THE REPUBLIC OF TURKEY

İSTANBUL KÜLTÜR UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

INDUSTRY 4.0 APPLICATIONS IN NIGERIA: EVALUATING THE PRACTICES VIA AN MCDM APPROACH

MASTER OF SCIENCE THESIS

by FAROUK AFOLABI

Department: Industrial Engineering

Program: Engineering Management

Supervisor: Assist. Prof. Duygun Fatih Demirel

JANUARY 2023

THE REPUBLIC OF TURKEY
İSTANBUL KÜLTÜR UNIVERSITY
INSTITUTE OF GRADUATE STUDIES

INDUSTRY 4.0 APPLICATIONS IN NIGERIA: Evaluating the Practices via an MCDM Approach

M.Sc. Thesis

by FAROUK AFOLABI
2000000366

Date of submission:	**January 2nd 2023**
Date of defence examination:	**January 18th 2023**
Supervisor and Chairperson:	**Assist. Prof. Duygun Fatih DEMİREL**
Members of Examining Committee:	**Assist. Prof. İlayda Ülkü** **Assist. Prof. Eylül Sezer**

JANUARY 2023

ACKNOWLEDGEMENT

I would like to express my gratitude to everyone who gave me the opportunity and possibility to complete this study. I want to specially thank my father for sponsoring education up till date, I cannot express my gratitude enough in this lifetime for his endless support and everything he has done for me, quality education is priceless and without him would not have had this opportunity to study in this great university, I love you so much daddy and I would also like to thank my mother she has been of great support to me from the beginning masters, not just this masters but in my life generally, she is the reason I am the man I am today she is my superhero.

Date: 2 January 2023 Farouk AFOLABI

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

A Controller system matrix

B Controller input matrix

£ Three-dimensional Euclidean Space

G Plant input matrix

Gj Plant disturbance input matrix

Üniversite	**: İstanbul Kültür Üniversitesi**
Enstitü	**: Lisansüstü Eğitim Enstitüsü**
Anabilim Dalı	**: Endüstri Mühendisliği**
Programı	**: Mühendislik Yönetimi**
Tez Danışmanı	**: Dr. Öğr. Üyesi Duygun Fatih Demirel**
Tez Türü ve Tarihi	**: Yüksek Lisans – Ocak 2023**

ÖZET

NİJERYA'DA ENDÜSTRİ 4.0 UYGULAMALARI: YÖNTEMLERİN BİR ÇOK AMAÇLI KARAR VERME YAKLAŞIMIYLA DEĞERLENDİRİLMESİ

Farouk AFOLABI

Açlık ve yetersiz beslenme, özellikle az gelişmiş ülkelerde en büyük endişe kaynaklarından biridir. Teknolojinin özellikle tarımsal ekonomide uygulanması, insanların refahına doğrudan katkıda bulunması ve artan küresel nüfusu beslemesi nedeniyle hayati bir konudur. Gıda güvenliğine ve gıda israfının azaltılmasına daha fazla önem veren bireylerin sayısının artmasıyla, daha iyi üretkenlik için tarımsal gıda sektöründeki tedarik zincirinin zincir boyunca izlenebilir olması gerekir. Elbette Tarım 4.0 uygulamaları sektördeki birçok soruna farklı çözümler getirebilir. Bu tez üretkenlik, tarım, Endüstri 4.0, tedarik zinciri ağları, çok kriterli karar verme (ÇKKV) yöntemleri ve gıda güvenliği hakkında çeşitli bilgiler sunmaktadır. Çalışmanın temel amacı, Nijerya'da tarım sektöründe uygulanacak en iyi Endüstri 4.0 uygulamasını seçmektir. Bu amaçla, alternatif seçim sürecinde dikkate alınabilecek kriterlerin önemi ve her bir alternatifin her bir kritere göre göreceli önemi hakkında üç uzman görüşü alınmıştır. Analitik Hiyerarşi Süreci (AHP) ve TOPSIS tabanlı hibrit bir metodoloji uygulanarak en iyi alternatif seçilmiştir.

Anahtar Kelimeler: Tarım 4.0, ÇKKV, Endüstri 4.0, AHP, TOPSIS

Bilim Dalı Sayısal Kodu: 90602

University	**: İstanbul Kültür University**
Instittute	**: Institute of Graduate Studies**
Department	**: Industrial Engineering**
Program	**: Engineering Management**
Supervisor	**: Assist. Prof. Duygun Fatih DEMİREL**
Degree Awarded and Date:	**: MS – January 2023**

ABSTRACT

INDUSTRY 4.0 APPLICATIONS IN NIGERIA: EVALUATING THE PRACTICES VIA AN MCDM APPROACH

Farouk AFOLABI

Hunger and malnutrition are major concerns in the world especially in under developed countries. The implementation of technology specifically in the agricultural economy is also a vital issue since it directly contributes to the wellbeing of people and feeding the global growing population. With an increasing number of individuals paying much attention to food security and reduction in food wastage, the supply chain in the agri-food sector has to be traceable throughout the chain for better productivity. Certainly, Agriculture 4.0 practices may provide different solutions to several problems in the sector. This thesis provides several insights on the productivity, agriculture, Industry 4.0, supply chain networks, multi criteria decision making (MCDM) methods and food security. The main purpose of the study is to select the best Industry 4.0 application to be implemented in agriculture sector in Nigeria. For this purpose, three experts are surveyed to obtain their opinions about the importance of the criteria that could be considered in the alternative selection process, and the relative importance of each alternative in accordance with each criterion. A hybrid methodology based on Analytic Hierarchy Process (AHP) and TOPSIS is implemented, and the best alternative is selected.

Keywords: Agriculture 4.0, MCDM, Industry 4.0, AHP, TOPSIS.

Science Code: 90602

1. INTRODUCTION

Especially Agriculture is one of the major industries of the global economy. Over the past centuries, agriculture has been a key means of the human survival, whereby people use to feed, boost economies and also earn a living. The increasing population of humans around the world has continued to pressure the agriculture sector in terms of feeding the population, because as time goes by the population is increasing rapidly, thus efficiency and productivity of farm produce is critical in feeding the emerging population of the world. The old conventional methods of agribusiness, where priority was on manufacturing food in large quantities; in the long term has led to a non-viable solution especially for a sustainable environment and society in general. Therefore, the conventional methods cannot provide a feasible result, hence new methods and processes need to be employed to provide a different solution. All the stakeholders in the agribusiness sector have to be considered. For example, the supply chain management, transportation, even the storage of food, all the processes involved from the harvesting of crops in the farm until food is bought from the final consumers have to be carefully scrutinized. According to Food and Agricultural Organization of The United Nations (FAO), suggest that approximately 40% of food is lost in the supply chain process, so changes have to be made in the supply chain to improve sustainability and transparency. Globalization has brought about various numerous advantages especially in the agriculture sector which provide benefits for the consumers, consumers now have access to variety of options, however this would also make the supply chain much more complex and the competition in the global marketplace to be fierce.

Technology has become a compulsory instrument in the industry of agriculture with an alarming increase in demand of agricultural productions and also with food wastage within the supply chain management in relation to increasing the productivity and sustainability. However, the 4th industrial revolution (Industry 4.0) comes into play with recent studies showing a fair amount of industries around the globe adopting this new technology for the purpose of enhanced productivity. The fourth industrial revolution (Industry 4.0) implies a steep trend towards digitalization, the implementation of data exchange and various technology for productions purposes such as Cyber-physical systems (CPS), Internet of Things (IOT), Big Data, Artificial Intelligence (AI), Smart Factories, Smart Manufacturing, Cloud Computing and Remote Sensors. This new drift towards embracing the forth industrial revolution in the manufacturing industries may be the solution for agri-business sector needs, especially in dismantling the major issues such as hunger, unproductivity, waste of natural resources, inefficiency, food wastage in supply chain management and sustainability issues.

Multiple criteria decision making (MCDM) is a procedure that links alternative performances across opposing, different, numerous quantitative and/or qualitative criteria's and provides an outcome requiring a consensus. The aim of MCDM is not to provide the best decision but to help the decision makers in choosing the most suitable alternatives or one alternative that can accomplish their requirement in a specific application area. Since the 1960s, numerous MCDM methods have been created, developed and implemented successfully in different numerous application areas. There are several MCDM methods available such as fuzzy decision-making, the analytical network process (ANP), the technique for order of preference by similarity to ideal solutions (TOPSIS), data envelopment analysis (DEA) and the analytical hierarchal process (AHP). MCDM has been one of the fastest growing problem areas in many disciplines. Over the past decade, many researchers have applied these methods in the field of industrial engineering in making decisions. All the methods are fairly capable of making decisions under unpredictability, and each one has its own benefits.

This research aims to establish more knowledge and evaluate activities in industry 4.0 applications in agriculture in Nigeria, using a multi criteria decision making method to obtain the most suitable alternatives that provide better solutions to solve major problems in food production and food transportation for the general population for instance, hunger, productivity, profitability, establishing a better supply chain in agriculture and also providing suitable ways of applying this technology effectively in the agricultural domain. In order to achieve the aim of this report the following research objectives must be fulfilled:

1. The research makes comparisons in industry 4.0 applications in agriculture in Nigeria.
2. The research helps decision makers in identifying the most suitable alternatives depending on each problem encountered in agriculture 4.0 in Nigeria.
3. This research shows alternatives to improve sustainability and efficiency in agriculture 4.0 in Nigeria.

The following questions are answered in this research:

1. Which industry 4.0 application is most suitable for the agriculture sector in Nigeria?
2. Is it possible to successfully implement industry 4.0 applications in Nigeria?
3. Which MCDM method would be easily adopted in industry 4.0 applications in the agricultural sector in Nigeria?
4. What better alternatives can be used in ensuring adequate utilization of agricultural products and processes from the old conventional methods being used in Nigeria?
5. What is the percentage (%) of industry 4.0 methods application in terms of agriculture, supply chain and sustainability in Nigeria?

This research is very important and beneficial to academic literature as well as Nigeria as a country because this is the first-time industry 4.0 applications using MCDM approaches are being applied in agricultural sector of Nigeria. Therefore, this can provide a new sustainable means of productivity, alternative methods and reduce food wastage and hunger in the country.

This research is centered on the industry 4.0 applications in agricultural domain in Nigeria using MCDM methods to find better alternatives that can boost the country's economy as well as sustainability and better standard of living for its people, therefore in line with aim, the subsequent objectives of the research must be fulfilled and the research questions must be answered. Additionally, the research is divided into five main chapters; The first chapter provides information about technology implementations in Agriculture and its key role in saving humanity from hunger, wastage of resources was examined as well as the old conventional methods of agriculture in Nigeria and the supply chain activities were discussed. It also presents an overview for the implementation of the trending industrial revolution (industry 4.0) in agricultural sector in Nigeria and it provides a brief background information on the MCDM method. The remainder of this report is organized as follows. Chapter 2 is divided into three subsections, where industry 4.0 background was reviewed, implementation of industry 4.0 in agriculture was reviewed and industry 4.0 technologies in agricultural supply chain was also reviewed. Chapter 3 shows the methods used in carrying out the research and the procedure of this study. Chapter 4 discusses the implementations and findings with some quantitative analysis. Chapter 5 summarizes the outcome of the report, gives the conclusion and provides future recommendations.

2. LITERATURE REVIEW

2.1. Industry 4.0 Background

The first industrial revolution (industry 1.0) around the period of 1750s which involved the use of steam engines and mechanization ultimately boosting production in the agricultural sector therefore reducing the amount of manual labor required in the manufacture of agricultural products, it started mainly in England then extended to Europe and USA (Ślusarczyk, 2018). The second industrial revolution (Industry 2.0) started in Europe and the USA which was around the period 1870s where the use of assembly lines in electricity was invented, a major development in chemical synthesis, agricultural processes were performed with big machines for collection of crops, which resulted in greater productivity and efficiency with agricultural production equipment. However, this major improvement came with some negative issues, for instance contaminations of chemical fields, less sustainable environment and degeneration of natural resources. The third industrial revolution (Industry 3.0) which was around the period of 1970s till present date involved the usage of information technology, nuclear energy, automation in manufacturing and also development in electronics such as transistors. Agricultural processes became much more efficient and machineries procedures were performed logically better (Akses, 2021). The fourth industrial revolution (Industry 4.0) which started around the period of 2010 till present date, it was first started in Germany (Mosconi, 2015 as cited in Roblek et al., 2016). This period involves the increasing trend towards digitalization, the implementation of data exchange and various technology for productions objectives. For instance, Artificial Intelligence (AI), Cyber-physical systems (CPS), Smart Factories, Internet of Things (IOT), Big Data, Smart Manufacturing, Cloud Computing and Remote Sensors. During this period, people started using flying drones, self-driving automobiles, having lectures without being physically present, programmable robots (Akses, 2021).

Figure 1 shows the industrial revolutions according to the period it began and ended relative to the time.

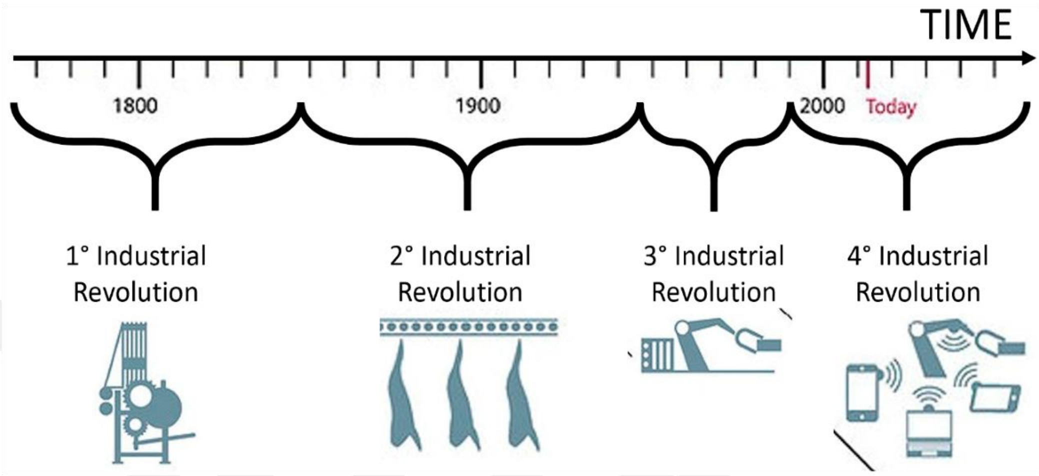

Figure 2.1 The industrial revolutions. Source:(Zambon et al.,2019)

2.1.1. Major Characteristics of the Forth Industrial Revolution (Industry 4.0)

The main aim of industry 4.0 is to develop an upper caliber of automation processes and a functional productivity and effectiveness in the human society. The leading characteristics are human-machine interaction (HMI), automation and robotization, digitization, production optimization, communication, data exchange and artificial intelligence. Where all these characteristics are solidly related with modern algorithms and internet technology (Roblek et al,.2016 as cited in Ślusarcyzk, 2018). The industry 4.0 main uses are commonly replaceable among each other and can be categorized into three (Zezulka et al.,2016):

- Digitization and combination of simple communication between humans, between machines and between humans and machines.
- Digitization of products and service which leads to disruptive innovations.
- Advanced market structures.

2.2. Agriculture 4.0

The Food and Agriculture Organization of the united nations (FAO) (2019) states that agriculture 4.0 revolution is the latest trend that may guarantee the future worldwide population requirements is fulfilled in terms of agribusiness. Technological changes and growth in farm yields represent different periods of the Agricultural revolutions. Agriculture is experiencing a rapid change towards the use of new technology around the globe, supported by the world leaders; thus, the new Agric technologies such as Big data, Artificial Intelligence, Internet of Things (IOT), Cloud Computing (CC) and Smart Farming may be crucial to attaining greater sustainable development and maximum productivity (Rose & Chilvers,2018). Aytekin, Ayas & Tumincin (2019) suggested that Agriculture is a dominant area in various parts of the world and Technology may progressively be an essential part of this dominant industry. Furthermore, the introduction of agriculture 4.0 technologies into the agriculture industry, for instance with Internet of things and cyber-physical systems several machineries would be prepared with digital sensors which leads to communication throughout the manufacturing operations between the equipment's and humans. The Industry 4.0 within the agricultural sector is often being alluded to as Agriculture4.0. Therefore, the swift development in advancing precision agribusiness and idealizing numerous conceivable future innovations to make modern value (Sponchioni, Vezzoni, Bacchetti & Pavesi as cited in Bigliardi, Bottani & Casella, 2020). Agriculture 4.0 in the global perspective are practically getting feasible with the improvement of the cultivating fields as data-driven activities and applications in different agricultural sectors (Spanaki et al., 2021). Implementation of Industry 4.0 in Agriculture is often used in related settings with terms such as 'Smart Farming', 'Digital Farming', 'Agriculture 4.0' and 'Farming 4.0' therefore subsequently used interchangeably (Yahya, 2018). The alarming increase in population, need to feed the population and natural circumstances are the main factors responsible for the change from basic agricultural methods to a smarter and data-oriented agricultural sector popularly known as agriculture 4.0 (Yahya, 2018 as cited in Spanaki, et al.,2021). New methods introducing an unrivalled artificial intelligence guided approach which involved high amount of data for resolving agribusiness problems (Miranda et al., 2019). Accenture (2020) states that the usage of digitization in the agri-business sector may double total profits margin from 55$ to110$ per acre of land. Irrespective of the phrase used digitalization in agriculture refers to the governance of duties on the farm, food system and the value chain network in general. Which lays emphasis on several data such as region, habits, usage, cost, climate, economic information and so on while using mobile devices, drones, satellites and tools to observe human behavior, animals, plants, sun, water and soil through constant observations, the data obtained is used to predict the future and make more detailed decisions (Klerkx et al., 2019). Figure.2 shows the progression and development of the various technologies used in agribusiness sector, which started from Agriculture 1.0 till present time Agriculture 4.0. It also shows the key features each agricultural revolution and major factors that supported each revolution.

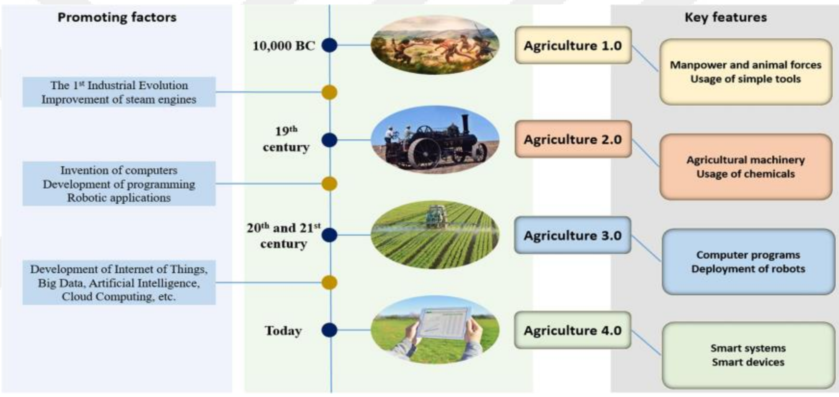

Figure 2.2. Agricultural revolutions. Source: (Zhai et al., 2020)

2.2.1. Key Stages of Agricultural Revolutions

Agriculture 1.0 was around the period of 1900s, it was a labor-oriented structure of agriculture with little productiveness. However, it was able to sustain the population yet it demanded a tremendous number of small-scale farms and one third of the population to be effective in the major agricultural manufacturing procedures. Agriculture 2.0 was a stage that started in the late 1950s when agri-business management processes involving novel equipment such as fertilizers, synthetic pesticides and better specialized machines that gained economical inputs, therefore developing productivity potential and outputs on different categories. Agriculture 3.0 can be called the precision farming era, it began around the period of 1990s. This phase began with military GPS-signals being accessible to civilians for general usage. Precision farming also provided results for manual navigations, data operations, sensing and control. The target changed from efficiency in terms of reducing cost to increasing earnings. Agriculture 4.0 started around the period of 2010s, this period entailed several evolutions of technology and a new improvement in precision agriculture. Some of the evolutions of technologies consisted of cheaper and better sensors, actuators, cloud related ICT systems, Big data insights, economical micro-processors, communication technology and smart control devices (Kovacs & Husti, 2018).

2.2.2. Internet of Things Technologies in Agriculture 4.0

The implementation of IoT in agribusiness sector provides further data sources showing agricultural essentials for example animals, soil and water with more data. Recent studies show the diversification of IoT into various platforms, this development leads to new integration structures that fit into different models depending each sector (Lee et al., 2018). However, the implementation of IoT platforms with agricultural problems may add to research challenges especially when data are stored in the cloud (Mocnej et al., 2018).

2.2.3. Big Data Technologies in Agriculture 4.0

The use of Big data in recent researches shows that in different sectors many relevant results are being provided (Lezoche et al., 2020). Big data technologies are key in the Agriculture 4.0 revolution, during this period many tools are connected with sensors to record data, different data science learning algorithms and machinery characteristics can be predicted as an outcome of analysis from the data. Big data empowers all farmers with a perspective of manufacturing frameworks and better decision-making techniques (Ozdogan et al., 2017). Further available agricultural information makes it obligatory to gather further evidence and it permits extra understanding. In recent times, expansion of investigative prospects for sensor data and agronomical data have developed with the use of artificial intelligence from machine learning (Weltzien, 2016).

2.3. Agri-tech for Food Supply Chain

The supply chain is an essential part of industry 4.0 investigation (Galati & Bigliardi, 2019). The digitalization trend has greatly affected various manufacturing sectors using actuators, sensors and processors which compile real information about machines, supporting communication among devices and also the sharing of information among all the stakeholders in the supply chain notifying them of different activities and helping them plan for the future demand (Schniederjans et al., 2020). Supply chain management in the agribusiness environment differs from the general industry of supply chain management because it deals with food products which are perishable items and time is a major factor to be considered, quality of food products is important, trailing and tracking of manufactured food along the supply chain and even temperature requirements of some food items (Claudine & Raja,2018). Supply chain involves the means or method used to deliver food from the manufacturer to the final consumer (Figure3). Most times these food products may be converted into sellable goods, refined products, packaged items and even reserved before it is distributed to a marketplace. In most under developed countries where infrastructure is poor, electricity is inadequate, transportation systems are missing, food loss is a crucial issue especially during the processing and post-harvest stages, more than 40 percent of food loss occurs (Farming First, 2021). The main purpose of analytical procedures within supply chain management is decreasing the unpredictability (Reiner and Trcka as cited in Zecca & Rastorgueva, 2014).

Agricultural supply chain can be described as relationship between the stakeholders in the agribusiness and the final consumers which involves data, the flow of food products and intelligence (Braun et al., 2018). The unique trend towards digitalization will transform the relationship within members of the agriculture supply chain, which would ultimately result in change in their business models, organization framework, ability to perform better and general acceptance of newer technologies; meaning steep integration for this sector. However, many industries have adopted the new technologies in their supply chain management but for the agricultural domain the transformation to these new technologies generally have been much lower than predicted, meaning they may be facing challenges or lack of participation (Soosay & Kannusamy, 2018).

Figure 2.3: Agricultural value chain diagram. Source: (Farming First, 2021)

Figure 2.3 shows the four major steps involved in a sustainable agriculture system chain. The first stage is the pre-production stage, this is where genetic resources are preserved for the development in productivity agricultural practices and it also involves technological innovations for the different agricultural inputs, for example crop safety products and fertilizers against future purposes. The second phase is the production phase, it involves different food loss challenges farmers must face during the growing and harvesting phase such as erratic weather, diseases, irregular market circumstances and pests. The third phase is the supply chain, this phase involves transporting, processing and storage of food among the agribusiness stakeholders, it also involves several innovative processes to add value and reduce wastage of food. The fourth stage is the consumption stage it involves how food is cooked, prepared and disposed by the consumers.

Effectiveness of a supply chain can be quantified mainly by the end users through the medium of acquiring the end product and the acceptance revolves around an aggregate of product quality, guarantees, pricing and food safety. The entire supply chain is accountable for food security and top-quality products which is of utmost importance and every member of the chain is responsible to an extent (Trienekens et al., 2012).

2.3.1. Major issues with Supply Chain

In recent times, many manufacturers in the supply chain environment face many challenges such as competitions in the global marketplace, lack of adaptability, market time planning demonstrated in Fig 2.4 (Arif-Uz-Zaman & Ahsan, 2014).

Figure 2.4 Key issues for supply chain firms**.** Source: (Arif-Uz-Zaman & Ahsan, 2014).

In recent history, globalization rules discarded the restriction of market borders. The small and medium enterprises are facing a difficult time in comparison to the large-scale enterprises especially in the manufacturing sector because they are unable to adapt to the latest technologies (Thomas & Trentesaux, 2013). A common problem is manufacturers being unable to predict demand and supply and reduction of lead time. The internet of things technology can solve this issue, which means there would be a great impact on the supply chain. For instance, this technology can determine the geographical location of consignments and speed of the automobile distributing them; so that users are aware of any irregular change in delivery time. IoT can also be used from a remote location to track the whereabouts of tools and machines (Qiu et al., 2015).

2.4. Multi Criteria Decision Making (MCDM)

Multi-Criteria Decision Making (MCDM) methods has been used extra ordinarily over the previous decades. Its importance generally has gained a massive boost in different application areas due to the development of new methods and the improvements of the existing methods (Velasquez & Hester, 2013). MCDM methods are commonly practiced in advent of the most advantageous solution when faced with various alternatives having numerous adverse and non-consistent decision criteria. The technique is popular tool for unfolding complex real-world issues due to their underlying ability to assess varied alternatives with reference to numerous decision criteria in order to select the most suitable alternative (Emovon & Oghenenyerovwho, 2020). MCDM is often considered as a perplexed outcome making mechanism which involves both quantitative and qualitative factors. Over the past decade, various MCDM methods and techniques have been suggested for selecting the best probable alternative (Mardani et al. ,2015). A literature review was carried out in relation to decision analysis and a search was implemented for popular MCDM approaches using google scholar and various databases. The following eleven MCDM methods were discovered throughout the review: Analytic Hierarchy Process, Fuzzy Set Theory, Multi-Attribute Utility Theory, Data Envelopment Analysis, Technique for Order of Preference by Similarity to Ideal Solutions, Simple Multi-Attribute Rate Technique, ELECTRE, PROMETHEE, Simple Additive Weighting, Case-based Reasoning and Goal Programming (Velasquez & Hester, 2013). The key procedures of MCDM are listed below:

Phase 1. Specify the issue, create options and build the requirements: A decision making issue begins with plainly explaining the obstacles, detecting options, determining the players, the aims, the objectives, all areas of strife, the disadvantages, the level of uncertainty and the major problem areas. Thus, the issue may be organized to specify the assessment needs.

Phase 2. Selecting the criteria value: The criteria weights reveals the significance of various criteria in the dilemma being reviewed and is often identified with the use of various methods. For example, the AHP method and the Sismos technique.

Phase 3. Building of assessment matrix: A procedure whereby the importance of the complication is removed from the complicated framework and declared in a means that the issue may sufficiently addressed.

Phase 4. Choosing the most suitable technique: A multi criteria approach should be chosen and tested in relation to the particular issues under review in structure of having a hierarchy for the alternatives.

Phase 5. Hierarchy of options: The options are ranked according to the importance and the most suitable substitute is proposed as a solution (Srisawat & Payakpate, 2016).

2.4.1. Analytical Hierarchy Process (AHP)

The AHP method is a MCDM method which permits and aid experts in organizing decisions criteria on a priority bases through a series of duo-wise similarities or contrasts. AHP has three fundamental assumptions that AHP depends on: (1) the ranking principle; this consist of creating a hierarchical tree with criteria, sub-criteria and alternative results, (2) the preference building convention and the uniformity convention (Stankovic, Gladovic & Popovic, 2019). AHP is a very useful method in decision making adopted in evaluating and selecting the most suitable alternatives. AHP is established on pairwise similarities using ratio measurement to show the strength of preference. This method was developed in 1980 by Dr. Thomas Saaty as a means to assist with fixing managerial and technical issues. The objective and aim of this method are to quantify relative preferences for an available batch of substitutes on a ratio scale, established on the decisions of a decision creator likewise the uniformity of the comparisons of options in the decision-making procedure. The process concurs well with characteristics of a decision maker because a decision maker bases judgment on experience and knowledge, then makes choices accordingly. The major strength in this procedure is that it coordinates tangible and intangible characteristics in a systematic way and provides simple and organized solutions to the decision-making process (Palcic & Lalic, 2009). AHP method was applied in a study in Malda district of India, to determine the chances and consequences of flood instances as well as the accessibility level, therefore preparing the risk zones in that area (Ghosh & Kar, 2018).

2.4.2. Élimination Et Choix Traduisant la Réalité (ELECTRE)

The acronym ELECTRE represents “Elimination Et Chiox Traduisant la Realite” which means elimination and choice expressing the reality. ELECTRE method can be described in simple terms as the conversion of a quantitative result to a more qualitative explanation (Yucel & Gorener, 2016). The introduction of this method was around mid-1960s, which was suggested by Benayoun Roy. The method is popularly used in the category of dominating methods of MCDM. The key purpose of the ELECTRE method is to place hierarchy on options under various criteria and appropriate application of outranking unity. Outranking procedures possess numerous operations in decision creating as well as engineering. ELECTRE is widely accepted for day to day issues because of its effective computational processes and intact logic. Shortly after introducing the initial model recognized as ELECTRE I, several other versions were developed for instance ELECTRE II, III, IV, IS and TRI. ELECTRE II and ELECTRE III are the most popular in terms of usage among the numerous ELECTRE versions. ELECTRE I and IS are created to solve decision issues while ELECTRE II, III and IV are mainly used for preference issues (Devi & Yadav, 2012). Decision support system is a structure usually used to help in supervision of decision making in various managerial aspects. ELECTRE method was adopted in a web-oriented application for a decision support system (Yanie et al., 2018).

2.4.3. Multi Attribute Utility Theory

Multi-attribute utility concept is the expansion of Utility theory created for aiding decision inventors in the selection of service valuation, after considering the options of the decision maker, which provides results through estimation of conditions in various attributes and joining single selections in deriving total utility estimates. Utility theory is used broadly in the development of a liaison among costs and utility obtained due to a distinct choice. Multi-attribute utility theory often associates the important leverages of direct scoring methods and optimization structures. In addition, scenarios whereby achievement is unpredictable, utility roles entail the characteristic of expected utility being used as a clue for analytical decision making (Mateo, 2012). A study used multi-attribute utility theory for the integration of several objectives and decision inventors' choices in rating a number of bridges (Bukhsh, Stipanovic & Doree, 2020).

2.4.4. Technique for Order of Preference by Similarity to Ideal Solutions (TOPSIS)

This method calculates the best alternative by applying distances to negative and positive results. This method was developed in 1981 by Hwang and Yoon. The procedure is quite easy and the solution process does not alter regardless of the number of decision criteria and options. Although the link between criteria are not studied in the estimation of the Euclidean distance, and vector normalization is often a prerequisite when solving issues that have different dimensions (Emovon & Oghenenyerovwho, 2020). This method is based on determining an optimal, anti-optimal result and it is also concerned with analyzing the distances of each alternative (Papathanasiou & Ploskas, 2018). A study was made to evaluate the level of good governance in European Union countries using the TOPSIS method. The research with the use of the MCDM method identified countries that have been successful in good governance in long term and also showed countries that have not been successful as well (Ardielli, 2019).

2.4.5. Utility Theory

Utility Theory was first introduced by the popular swiss mathematician Daniel Bernoulli in the 1736, with the aim of analyzing the behaviors of decision makers in management of risks, therefore observing the ramifications of decision making. (Shi & Wang, 2019). Utility is a type of evaluation of individuals and abstract mental feeling. It is the special benefit, emotion or trade off response of decision inventors to the expected and anticipated losses of specific risk scenarios. It can show the decision-makers distinct risk scenarios in risk management selections. Utility measures are often known as utility value or utility. Utility index usually quantifies some complex qualitative conditions that are challenging to evaluate, in order to be able to differentiate them. The valuation of utility values ranges between 0 and 1, therefore, $0 \leq U \leq 1$. For numerous outcomes that may occur with a decision issue, if the decision maker believes they are not different, they will be considered to have the same utility value. A paper successfully applied utility theory for modeling a US-China trade conflict, it attempts to discuss the ideal strategic options and also analyze the conflict mathematically (Zhang and Chang, 2020).

2.4.6. Data Envelopment Analysis (DEA)

Data Envelopment Analysis was created by Charnes, Cooper and Rhodes in 1978, they also established the simple DEA model popularly known as CCR DEA model, which is a novel approach of calculating every performance of decision-making groups using several information and productivity. Subsequently, multiple types have been created such as: the BCC DEA model which considers variable return to ratio, the Banker and Morey version which comprises of subjective information and yields, the additive model which is non-spiral, and the Golany and Roll type including restrained statistics that influences a unique variety of principles (Popovic et al., 2020). DEA is a method in which estimation of the relative ability of decision making is defined by various attributes with unequal information and production. The outcome majorly depends on analyzing the principles set applied. Furthermore, selection of criteria set is a very key stage in this method because as effort of estimation surges significantly so does the quantity of data also increase. In numerous educational programs, academics regard inputs and outputs as “givens” and afterwards handle the DEA procedure (Mazumder et al., 2018). A study was made using data envelopment analysis in combination with AHP and conjoint analysis to classify teacher accomplishment in university. The procedure of assessment is intricate because it includes review of subjective and objective performance estimation. The performance assessment in the existence of several contrasting criteria is performed using DEA and the answers rely importantly on their values, selections and the weights appointed to them (Popovic et al., 2020).

2.4.7. Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE)

The PROMETHEE method was first created in the early 1980’s by Brans Jean Pierre, this is also an outranking procedure usually for substitutes of a definite set that is rated and selected. The method was further developed in 1985 by Brans and Vincke. Under multiple criteria a certain set of fixed options are evaluated. Every independent benchmark is weighted and the most suitable preference should be selected. After the introduction, there has been six other methods developed within the PROMETHEE tribe which are used in the providing solution to MCDM problems. Each of the PROMETHEE methods has a unique role with respect to the characteristics of every problem. PROMETHEE I was first designed for limited ranking of the substitutes. PROMETHEE II was established to implement a complete ranking of the alternatives, an extended version of this method known as PROSA (PROMETHEE for sustainability Assessment) method was also developed to derive lower rank of criteria benefits. PROMETHEE III was developed to improve negligence in order to rank the options according to extending intervals. PROMETHEE IV was proposed for either partial or complete substitutes ranking when there is a continuous collection of possible answers. PROMETHEE V was created for situations whereby issues are continuous by way of using constraints to magnify the overall outranking progress of the options. PROMETHEE VI was designed in a way that allows the decision maker preferences to be included, so this method permits variation in magnitude of criteria (Brans, Vincke & Mareschal, 1986 as cited in Sitorus et al. 2019). A research was made using PROMETHEE method to select contractor for renovating the cultural heritage buildings. Cultural heritage buildings performance is complex work, so choosing a contractor for heritage buildings security and renovation is a challenging task. The AHP technique was used to decide key criteria and their weights for every criterion. The PROMETHEE method was applied for choosing the most efficient and reliable cultural heritage contractor's alternative.

2.4.8. Goal Programming Methods

Goal programming (GP) is an essential type of MCDM method, which is broadly used in analyzing and solving applied problems that involve contradictory objectives. It was originally introduced by Charnes et al around mid 1950s as an expansion of linear programming methods. There are complications in numerous real-world issues because of difficulties faced when providing solutions to issues with a particular target and modelling. GP method is a distance-oriented procedure which develops numerous ambitions by decreasing the irregularities in purposes from the desired aim the decision maker established. Furthermore, after the irregularities are forced to nothing the model aim may be concluded, the irregularities may be good or unfavorable which shows over achievement or underachievement of the aims subjected to various constraints (Colapinto, Jayaraman and Marsiglio, 2015). A study was carried out for the investigation of the new version of the multi-objective on the basis of ratio analysis (MOORA) together with goal programming method to provide solutions to issues concerned with loaning decisions. GP was applied in solving the multi objective lending issue by reviewing all continuous related information or data, constraints and objectives. While the MOORA method was used to gather economic percentage in other terms distinct information (Ic, 2020).

2.5. The Usage of MCDM methods in Industry 4.0 Applications

Green supply chain management (GSCM) is a management style technique which integrates the concept of thinking in an environmental way in every supply chain activity such as selection of materials, design of products, manufacturing process and purchases across capable companies for the purpose of gaining extra profits as well as improving their ecological work through the reduction of consequences in ecosystem hazards (Mishra et al., 2019 as cited in Calik, 2021). Suppliers play an important role for companies in developing their environments. Numerous companies have observed the green supplier selection (GSS) issue when creating GSCM. An automated, novel or intelligent supply chain is developed through gathering additional technology and data in modernized supply networks. Presently in the fourth industrial revolution, companies are searching for different novel approaches to develop operations of supply chains and they are ever more dependent on the use of industry4.0 technology such as digital supply chain, cloud systems, big data analysis and the Internet of Things (IoT). Multi-criteria decision-making methods may be an appropriate tool used in solving the GSS problem and also comparing alternative suppliers (Calik, 2021). For example, Calik (2021) made a study creating a hybrid decision making group using two MCDM methods; AHP and TOPSIS approach based on Pythagorean fuzzy sets (PFS) for GSS from the Industry 4.0 era. In selecting the supplier, they find most appropriate, a three step MCDM technique is joined and applied. Initially, a committee is formed to assemble the idea of all professionals, afterwards the GSS characteristics are limited based on the information analysis and experts' notions from the fourth industrial revolution perspective. Secondly, Pythagorean fuzzy AHP were used to obtain the criteria weights obtained. Finally, Pythagorean fuzzy TOPSIS were used to rank the potential suppliers.

2.6. The Usage of MCDM methods in Agriculture sector

MCDM methods are widely used in the agricultural sector for various important activities specially to assist inventors of decision in providing the most suitable solutions and alternatives. A study was carried out by Mustafa et al. (2011), whereby the combination of the Geographical Information System (GIS) and Analytical Hierarchy Process (AHP) were used to estimate the appropriateness of agricultural areas for various crops both in winter and summer seasons in India. Mendas and Delali (2012) designed a dimensional decision assistance structure through the combination of GIS and ELECTRE Tri (ELimitation Et Choix Traduisant la REalité), which enables the arrangement of agricultural land use suitability maps. According to Golfam et al. (2019). A study was made in order to ascertain the most suitable situation acclimatizing to modify climate in agronomy using two MCDM methods, Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for a period of 30years.

3. METHODOLOGY

In this section, the methodology to be applied is described in detail. The steps of the methodology are provided in the flowchart below in figure 5

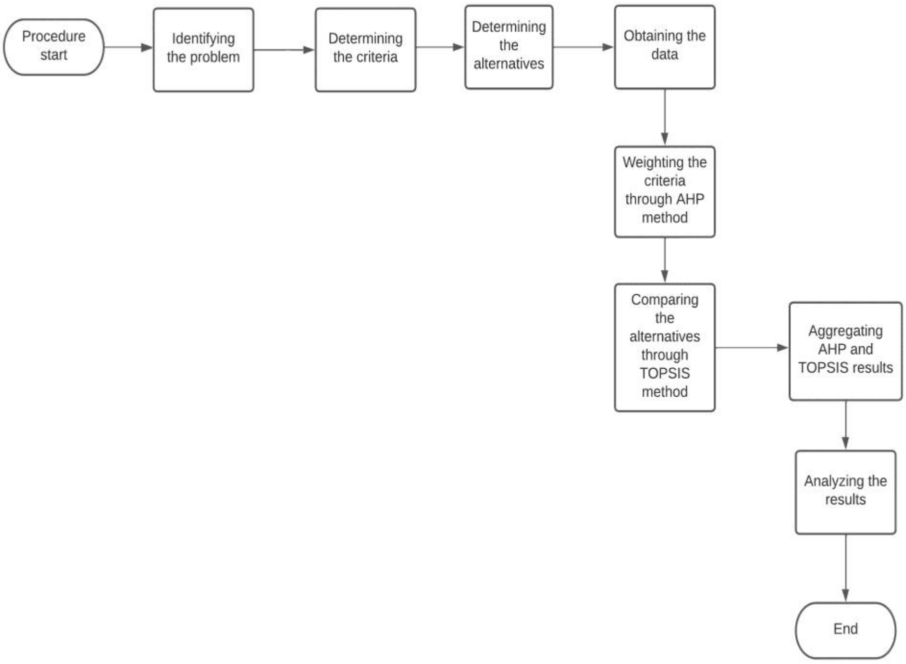

Figure 3.1 Flow chart describing the methodology.

3.1. Identifying the problem

The steady increase in the general population requires an increase in food production to tackle hunger, however the old conventional methods of agriculture have not provided a feasible solution to hunger, food wastage, productivity and sustainability especially in under developed countries and recent drift towards digitalization may yield positive results to these issues and provide a better supply chain network.

3.2. Determining the criteria

Five criteria and numerous sub criteria were selected in this report, which were determined to be the most relevant in the literature review to the objectives of this thesis. The criteria and sub-criteria are listed below as follows:

1. Cost – purchase cost & operation cost
2. Technological capability - innovation & technology.
3. Sustainability - economic impacts, social impacts & environmental impacts.
4. Resource consumption.
5. Quality.

3.2.1. Cost

Cost is one of the important criteria in the literature review when considering many decision-making problems especially in industry 4.0 implementations. Cost can be measured numerically through real data from several articles and thesis related to the objectives of this report. Cost was one of the key criteria in supplier selection factors identified in healthcare industries (Miah, Ahsan & Msimangira, 2013). Additionally, two sub criteria emerged namely purchase cost and operational cost.

3.2.2. Technological capability

Technological capability represents the ability of a company or organization using a technology beyond the present company’s technological ability. The more advanced the technological capability the higher inclination for technology transfer, research and development. This criterion can be measured through expert opinions-based data. Technological capability was a major criterion in the interactive trade decision making research which used an application case of novel hybrid MCDM (Wang, 2012). There are two sub-criteria under this criterion namely; innovation & technology.

3.2.3. Sustainability

Sustainability can be defined as taking advantage of resources to match the current needs without disrupting the future generation ability to match those needs. There are three sub-criteria under the criteria namely; economic impact, social impact and environmental impacts. Sustainability was used as a criterion in an AHP based multi criteria model for sustainable supply chain development in the renewable energy sector (Mastrocinque et al., 2020). This criterion can be measured through expert based opinions data.

3.2.4. Resource consumption

This refers to the level of resources that a technology implementation will consume if applied. Resource consumption was used as a criterion in the application of AHP and corrective factors for the determination of best available techniques and emission limit values at installation level: A case study in four cement installations (Santonja et al., 2019). This criterion may be measured through expert based opinions data.

3.2.5. Quality

Quality means effectiveness or usefulness of products or services to the consumers. It can be measure through expert opinions-based data. It was one of the key criteria in supplier selection factors identified in healthcare industries (Miah, Ahsan & Msimangira, 2013).

3.3. Determining the alternatives

Four alternatives were considered in the thesis. which were considered to be suitable in meeting the objectives of this thesis after several extensive literature reviews, they are listed below as follows;

1. Cyber physical systems
2. Big data & Cloud computing
3. Smart sensors & robotics

3.3.1. Cyber physical systems (CPS)

A CPS can be described as combination of computer usage for research with physical processes. It uses smart sensors and actuators to connect computational structures and the real physical world. (Fresco & Ferrari, 2018). CPS may be considered a new dimension of systems under automatic independent nature. It is different from the old conventional robot automation; whereby industrial robots carry out a repetitive task under certain conditions and boundaries. CPS can provide a more advanced and accurate agricultural system by collecting significant information in terms of climate, soil, plant diseases, pest and other data. Food security and precision agriculture may experience tremendous growth and progress through the unification of CPS technologies with food systems and agricultural systems (Sadiku et al., 2020). A large number of cooperative sensors was used within a CPS structure to upgrade the use of pesticides with accurate spraying . An open geographical web service integrated with CPS infrastructure was suggested to collect, combine, process and deliver monitored information from the physical sensor areas over the World Wide Web. (Channe et al., 2015).

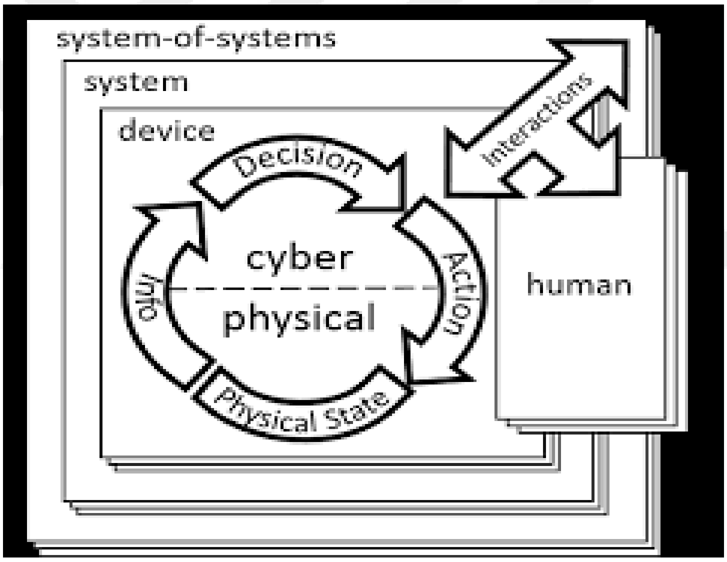

Figure 3.2 CPS framework conceptual model (NIST, 2017)

3.3.2. Big data and Cloud computing

Big data is often known as a combination of analytics and technology that can retrieve and process data in a faster and more effective way to help decision making. The addition of Big data in the agricultural sector develops into smart farming. Smart farming refers to an idea of management of farm using data analytics, sensors, GPS, drones, ICT, IoT, communications system, robotics, etc. With the implementation of all these technologies, agriculturist can gather data, observe the field conditions without physically being in the field and produce better decisions. Smart farming is key in facing threats of production in agriculture in terms of sustainability, food security and productivity (Sadiku, Ashaolu & Musa, 2020). Big data is used in the management of supply chain of agricultural products to reduce the production cost. Cloud computing unites a tremendous amount of IT resources at the backend with people through adequately defined interface. Cloud services generally include storage, special hardware resources, processors, network and various services. Cloud is provided to users through three service models namely; software as a service (SaaS), platform as a service (PaaS) and infrastructure as a service (IaaS). Cloud computing allows resources to be shared with a cheaper cost. Cloud computing in agriculture has various benefits, for instance large scale information storage, provide easy solutions to farming queries, cloud agro system where overall information related to agriculture is computerized and monitored, cheap cost access to IT services (Goraya & Kaur, 2015).

3.3.3. Smart sensors and robotics

Smart sensors can be explained as the advanced development of the wireless sensor. Smart sensors usually involve advanced techniques such as artificial intelligence, which plays a vital role in smart agriculture and remote sensing. The smart sensor in the agricultural sector can produce benefits through adequate crop quality analysis, crop classification, measurement of soil moisture, evaluation of weather condition & the use of robots for weed eradication and harvesting. The role of smart sensors is key in agriculture because productivity is highly enhanced and sustainable growth is also improved, which ultimately helps empower farmers globally (Ullo & Sinha, 2021). Robotics have been developed in agriculture to carry out precision farming tasks and to help people in specific tasks or replace them. These robots come in two main types: I) automatic mobile robots and ii) “robotic smart” equipment that are used by a vehicle. The automatic mobile robots involve robotizing of old agricultural tools such as sprayers, tractors and harvesters through the use of GPS automated guidance systems. They can operate automatically in aligned rows inside fields while an operator inspects and carries out cultivation assignments. While the “robotic smart” equipment’s are used for numerous applications like transplanting, mechanical weeding, lettuce thinning, fruit harvesting, wine trimming in grape plantations and fruit farms (Vougioukas, 2019).

3.4. Obtaining the data

In this report, data was obtained majorly through the use of real numerical data and expert opinion-based data.

3.5. Weighting the criteria through AHP method

The AHP method was used to determine the weights of the criteria for this report. This is an adequate technique for calculating the importance of the criteria especially when decision making is important. The implementation process of AHP method uses four steps (Songur, 2018).

Firstly, the decision issues are explained and a ranking structure is created; the effective criteria related to the issues are selected and the ranking structure which consist of different levels are established. For every issue, a ranking structure including criterion, possible sub-criteria stages & alternatives are established.

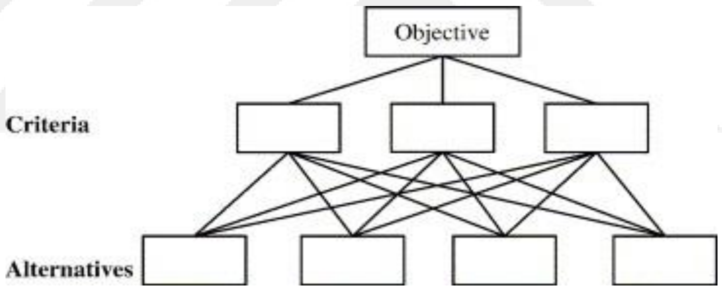

Figure 3.3 Ranking structure

Secondly, comparisons of pair-wise matrix are developed among the criteria; the pair-wise similarity is carried out by querying experts or decision makers, with questions such as which criterion is more relevant or valuable to the main aim of the decision and compare them according to rating scale as shown in Table 1. AHP calculates the significant weights of each criteria by using P = $\|P_{ij}\|$ (*i, j= 1,2,…,m.* experts then compare the estimation criteria R_i and R_j (*i, j = 1,2,…, m)* where m is the total number of criteria compared. In an optimal scenario, the values of the matrix will show the relationships between the unknown criteria weights:

$$P = \begin{bmatrix} P_{11} & P_{12} \cdots & p_{1m} \\ P_{21} & P_{22} \cdots & p_{2m} \\ \vdots & & \vdots \\ P_{m1} & P_{m2} \cdots & p_{mm} \end{bmatrix} = \begin{bmatrix} \frac{\omega_1}{\omega_1} & \frac{\omega_1}{\omega_2} & \cdots & \frac{\omega_1}{\omega_m} \\ \frac{\omega_2}{\omega_1} & \frac{\omega_2}{\omega_2} & \cdots & \frac{\omega_2}{\omega_m} \\ \vdots & & & \vdots \\ \frac{\omega_m}{\omega_1} & \frac{\omega_m}{\omega_2} & \cdots & \frac{\omega_m}{\omega_m} \end{bmatrix} \quad (3.1)$$

The comparison is qualitative and easy to implement. It shows which criterion is more significant and the priority level. This method permits qualitative evaluation from experts to be changed to quantitative ones. The matrix P is an inverse symmetrical matrix, that is P_{ij}=1/P_{ji}. Furthermore, the part of the matrix above the main diagonal or below it can be filled up. The number of elements compared is *m(m-1)/2 i.e the total number of the comparison matrix elements is equal to m*^{2}.

The estimation of the criteria ranges from P_{ij} = 1, when R_i and R_j and equally important, to P_{ij} = 9 when the criterion R_i is much more important than R_j in respect to the research aim. (Saaty, 2008).

In a real case, the inverse symmetry of matrix P is obvious, the elements of any duo matrix rows or columns will correspond. For instance, the connection between the first and second column elements are described below:

$$\frac{P_{i1}}{P_{i2}} = \frac{\omega_i}{\omega_1} \div \frac{\omega_i}{\omega_2} = \frac{\omega_2}{\omega_1} \quad (i = 1,\ldots, m). \quad (3.2)$$

Scale	Meaning
1	Equal importance
3	Average importance
5	Strong importance
7	Verified importance
9	Utmost importance
2, 4, 6, 8	Intermediate values

Table 3.1: Numbered rating of the AHP method

Thirdly, estimation of the criteria weights; building of normalized matrices happens here. The normalized matrix is derived through the division of each horizontal amount by the specific column aggregate. After the normalized matrix, the average of every series is derived and the derived values are the key weights for every criterion.

The situation needed for a matrix to agree can also be conveyed calculation terms. In a model case, with the use of equality (1), matrix P is multiplied by the column of the weights. i.e the transposed row $\omega = (\omega_1, \omega_2, \dots, \omega_m)$^T :

$$P\omega = \begin{bmatrix} P_{11} & P_{12} \cdots & p_{1m} \\ P_{21} & P_{22} \dots & p_{2m} \\ \vdots & & \vdots \\ P_{m1} & P_{m2} \dots & p_{mm} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \omega_2 \\ \vdots \\ \omega_m \end{bmatrix} = \qquad (3.3)$$

$$P\omega = \lambda_{max}.\,\omega \qquad (3.4)$$

Where P = m dimensional comparison matrix i.e number of criteria compared, λ_{max} = largest eigenvalue of P and

ω = eigenvector corresponding to λ_{max}.

$$\omega_i = \sum_{i=1}^{m} Pij^* /m \qquad (3.5)$$

Finally, the consistency ratio (CR) of the comparison matrices are reviewed; the consistency is measured because the precision of the procedure is to be tested. If the comparison matrix is inconsistent, for instance the CR is greater than 10%, then the values of weights cannot be used. The CR coefficient is estimated after the Consistency Index (CI). The consistency index (CI) is defined to estimate the inconsistency in the pairwise comparison matrix A.

$$CI = (\lambda \max - m)/ (m - 1) \qquad (3.6)$$

Next the CR is derived by dividing the CI value by the random consistency index (RI).

$$RI = 1.98\ (m - 2)/ m \qquad (3.7)$$

The RI value is related to the dimension of the matrix listed in Table 2.

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49

Table 3.2: Random consistency index R.I

(CR) = CI / RI (3.8)

The consistency test is achieved when the CR is calculated. If the CR is less than 10%, it means the data is consistent. If CR is greater or equal to 10%, the data is inconsistent, the original values in the pairwise comparison matrix should be reevaluated and revised.

3.6. Comparing the alternatives through TOPSIS method

The alternatives were analyzed with the use of an MCDM technique known as TOPSIS. TOPSIS method is established with the orientation that the selected or most suitable alternative must have the nearest distance to the optimal solution and also the furthest distance from a geometrical perspective with the use of Euclidean distance to estimate the relative closeness of an alternative alongside the ideal solution (Indahingwati et al., 2018). The Technique for Order of Preference by Similarity of Ideal Solutions (TOPSIS) can be described in steps, which are described below: (Ozcan, Unlusoy & Eren, 2017).

Step 1: Build the decision matrix.

The created matrix includes m alternatives and n criteria with the junction of each criteria and alternative provided as x_{ij} and thus have a matrix$(x_{ij})_{\mathrm{mxn}}$.

Step 2: Create a normalized decision matrix.

Normalization is built to attain scales that are comparable. The vector normalization is explained below.

$Rij = aij / \sqrt{\sum_{k=1}^{m} aij^2}$ $i = 1,2,\ldots,m$ and $j = 1, 2, \ldots, n$ (3.10)

Step 3: Estimate the weighted decision matrix.

When the normalized decision matrix is formed, afterwards the weight of the normalized decision matrix V is calculated;

$V_{ij} = w_j \times r_{ij} \forall_i, j, w_j$ is the weight of criterion j. (3.11)

Step 4: Identify the optimum and the negative optimum solution.

V+ = $(max_i\ vij \mid j \in J), (min_i\ vij \mid j \in J)$ (3.12)

$V^- = (min_i \ vij \mid j \in J), (max_i \ vij \mid j \in J)$ (3.13)

The optimum solution consists of the one closest to the best alternative whereas the negative optimum solution consists of the worst performance values.

Step 5: Estimate the distance between each alternative from the optimum best and least optimum solution.

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(vij - vj^+)^2} \quad i = 1,2,3,\ldots, m. \quad (3.14)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}(vij - vj^-)^2} \quad i = 1,2,3,\ldots, m. \quad (3.15)$$

Step 6: the rank of the alternatives is determined by comparing C^+ values.

$C_i^+ = S_i^- / (S_i^- + S_i^+)$ i = 1,2,3,…, m. (3.16)

Where $0 \leq C_i^+ \leq 1$.

3.7. Aggregating AHP and TOPSIS results

AHP was used to calculate the importance of the criteria weights and the numerical weightage. TOPSIS was used to select and rank the alternatives for the most suitable one in Nigeria while using the criteria weights from AHP, this is how the two multiple criteria decision-making methods were combined for making decisions in this thesis. The weights of the three experts are equal to each other

(w1 = w2 = w3 = 1/3) (3.17)

The weights of criteria for each expert were separately found using AHP.

Then the weight of criteria of each expert were combined into a single criteria weight vector.

W_{cij}= weight of criterion i for expert j (3.18)

For each i apply

$W_{ci} = 1/3 \sum_j W_{cij}$ (3.19)

For each experts' alternative comparisons, the common weights of criteria that were found in equation 3.3. Then apply TOPSIS for each expert separately.

We assume the weight of alternative K is Wak.

W_{ak} = 1/3 $\sum_j W_{akj}$ (3.20)

Where W_{akj}= weight of alternative K for expert j which is found by TOPSIS.

3.8. Analyzing the results

The alternative with the highest performance score is going to be ranked first, which means this is the most preferred choice based on criteria used in this thesis and in also in real life applications, followed by the next highest which would be the second preferred alternative and finally the least preferred alternative would be ranked third.

4. IMPLEMENTATION AND RESULTS

In this section, the methodology is being implemented using numerical data from three experts. The experts were contacted virtually through numerous zoom meetings and they filled excel forms, rating and ranking the criteria and alternatives which were implemented in this project. The implementation aided in the selection of the most suitable alternatives in the application of industry 4.0 in the agricultural sector of Nigeria. The application of these steps involves three alternatives (cyber-physical system, big data & cloud computing and smart sensors & robotics) against criteria (cost, technological capability, sustainability, resource consumption and quality).

Adequate information such as the place of work, nationality, experience, gender and general information of the experts who provided numerical data for calculations of this report is displayed in table 4.1 below.

	Expert 1	Expert 2	Expert 3
Title	Managing Director	Agric extensionist and biochemist	Senior solution sales executive digital supply chain
Gender	Male	Male	Female
Age	Adult	Adult	36
Field of expertise	Agric Agronomy	Animal Production	Sales of supply chain and technology services
Place of work	MANR/KWADP, Ilorin, Nigeria.	Ministry of Agriculture, Nigeria.	SAP, Turkey.
Years of Experience	35	38	13

Table 4.1: Information about experts used in providing the results

4.1. Weighting of the Criteria through AHP and TOPSIS method

The numerical value of pairwise comparison matrix derived from the opinion of first expert is shown in table 4.2. At first glance cost appears to be the most important criteria in comparisons to the other criteria followed by sustainability, however resource consumption appears to be the least important criteria.

Criteria	Cost	Technological capability	Sustainability	Resource consumption	Quality
Cost	1	4	2	7	5
Technological capability	0.25	1	0.33	3	2
Sustainability	0.5	3	1	5	3
Resource consumption	0.14	0.33	0.2	1	0.5
Quality	0.2	0.5	0.33	2	1

Table 4.2: Pairwise comparison matrix for expert 1

The numerical value of pairwise comparison matrix derived from the opinion of second expert is shown in table 4.3 below. At first glance it can be noticed that cost has a verified importance in comparison with technological capability, followed closely by quality with a strong importance and then resource consumption with a below average importance however cost in comparison to resource consumption is less important. Resource consumption is a

Criteria	Cost	Technological capability	Sustainability	Resource consumption	Quality
Cost	1.00	6.00	0.33	4.00	5.00
Technological capability	0.17	1.00	0.14	0.33	0.50
Sustainability	3.00	7.00	1.00	5.00	5.00
Resource consumption	0.25	3.00	0.20	1.00	0.50
Quality	0.20	2.00	0.20	2.00	1.00

Table 4.3: Pairwise comparison matrix for expert 2

The numerical value of pairwise comparison matrix derived from the opinion of third expert is displayed in Table 4.4. It can be observed from the table sustainability had the lowest numerical value in every pairwise comparison except from its duo with sustainability, which means it had less importance in comparison to the other criteria for the third expert.

Criteria	Cost	Technological capability	Sustainability	Resource consumption	Quality
Cost	1	3	3	5	1
Technological capability	0.33	1	3	2	1
Sustainability	0.33	0.33	1	0.50	0.50
Resource consumption	0.2	0.5	2	1	0.25
Quality	1	1	2	4	1

Table 4.4: Pairwise comparison matrix for expert 3

The calculated numerical results of the random index, λ_{max}, consistency index and consistency ratio is shown at table 4.5. The consistency ratio was less than 0.10 which means the matrix calculations were feasible for expert 1.

Random index	1.188
λmax	5.10791219
Consistency index	0.02697821
Consistency ratio	0.0227088

Table 4.5: Random index and consistency ratio for expert 1

The calculated numerical results of the random index, λ_{max}, consistency index and consistency ratio are shown in table 4.6. The consistency ratio was less than 0.10 which means the matrix calculations were feasible for expert 2.

Random index	1.188
λmax	5.40831936
Consistency index	0.10207984
Consistency ratio	0.0859

Table 4.6: Random index and consistency ratio for expert 2

The numerical results of the random index, λ_{max}, consistency index and consistency ratio for expert 3 are shown in Table 4.7 below. The consistency ratio was less than 0.10 which means the matrix calculations were feasible for expert 3. The consistency ratio of the third expert had the smallest consistent ratio among all three experts which means the calculations and matrices was the best amongst all experts. The consistency index is also the smallest among the three criteria.

Random index	1.188
λmax	5.324402497
Consistency index	0.081100624
Consistency ratio	0.068266519

Table 4.7: Random index and consistency ratio for expert 3

4.2. Comparing the alternatives through TOPSIS method

The rating for the TOPSIS method used in this project was 0 (worst) and 10 (best).

The TOPSIS ratings from the first expert are shown in table 4.8. The expert ranked cyber-physical systems the highest in terms of cost and resource consumption, big data & cloud computing were ranked the highest in quality and smart sensors & robotics were ranked highest in technological capability.

	Cost	Technological capability	Sustainability	Resource consumption	Quality
Cyber- physical systems	8	9	3	10	9
Big data & Cloud Computing	4	8	3	9	10
Smart sensors & robotics	3	10	5	9	7

Table 4.8: TOPSIS results of expert 1

The TOPSIS ratings provided by the second expert is displayed in table 4.9. The second expert rated Big data & Cloud computing in terms of cost the highest which means that the expert believed it to be the most preferred option in cost terms. Smart sensors and robotics were the least preferred in terms of resource consumption which means the expert believed it would consume majority of resources in Nigeria. Cyber-physical systems has the lowest score in terms of technological capability among the other alternatives which means the ability to implement this alternative in Nigeria is low compared to the other alternatives.

	Cost	Technological capability	Sustainability	Resource consumption	Quality
Cyber-physical systems	8	8	7	6	6
Big data & Cloud Computing	9	9	8	7	6
Smart sensors & robotics	6	8	6	5	8

Table 4.9: TOPSIS results of expert 2

The TOPSIS ratings from expert 3 is shown in table 4.10 below, it can be observed that the ranking for big data & cloud computing are the highest ranking for cost and resource consumption which means it would be cheapest and most affordable if implemented in Nigeria against the other alternatives. it also ranked cyber-physical systems highest in technological capability which means this would be the easy to apply with the current innovations and technology standard in Nigeria in comparison to the other alternatives and smart sensors & robotics were the highest ranked in terms of the quality criteria which means the implementation of this alternative would provide the highest standard compared to the other alternatives.

	Cost	Technological capability	Sustainability	Resource consumption	Quality
Cyber-physical systems	5	8	7	4	8
Big data & Cloud Computing	9	6	6	9	7
Smart-sensors & robotics	5	7	7	6	8

Table 4.10: TOPSIS results of expert 3

The normalized decision matrix, optimum solution, negative optimum solution, the estimated distance between each alternative from the optimum best, the estimated distance between each alternative from the optimum worst, performance rating and the ranking for the first expert, which is displayed in table 4.11 below. At first glance cyber physical system has a very low estimated distance value between each alternative from the optimum best and a very high estimated distance between each alternative from the worst optimum solution, hence it has the highest performance score and ranked the most preferred alternative. Cloud computing has a high estimated distance value between each alternative from the optimum best and a low estimated distance between each alternative from the worst optimum solution, therefore it results in an average performance score and it is ranked the second preferred alternative. Smart sensors and robotics has a very high estimated distance value between each alternative from the optimum best and a very low estimated distance between each alternative from the worst optimum solution, which results in a low performance score and it ranked third which is the least preferred alternative.

	Cost	Technological capability	Sustainability	Resource consumption	Quality	S+	S-	Ranking score
Cyber-physical system	0.31	0.07	0.128	0.049	0.09	0.013	0.213	0.94
Cloud computing	0.16	0.065	0.128	0.045	0.10	0.156	0.098	0.39
Smart sensors & robotics	0.17	0.08	0.214	0.0445	0.07	0.214	0.016	0.07
V+	0.311	0.08	0.128	0.049	0.099			
V-	0.117	0.065	0.214	0.045	0.069			

Table 4.11: Normalized decision matrix for expert 1

The normalized decision matrix, optimum solution, negative optimum solution, the estimated distance between each alternative from the optimum best, the estimated distance between each alternative from the optimum worst, performance rating and the final ranking for the second expert, which is displayed in table 4.12 below. At first glance, it can be seen cyber physical system has a lower estimated distance value between each alternative from the optimum best than the estimated distance between each alternative from the worst optimum solution, hence it has an average performance score and it is ranked the second most preferred alternative with a score close to the second alternative. Cloud computing has a low estimated distance value between each alternative from the optimum best and a high estimated distance between each alternative from the worst optimum solution, therefore it results in the highest performance score among the other alternatives and it is ranked the first preferred alternative. Smart sensors and robotics have a high estimated distance value between each alternative from the optimum best and a low estimated distance between each alternative from the worst optimum solution, which results in a low performance score and it ranked third which is the least preferred alternative.

	Cost	Technological capability	Sustainability	Resource consumption	Quality	S+	S-	Ranking score
Cyber-physical system	0.218	0.070	0.161	0.046	0.077	0.045	0.055	0.545
Cloud computing	0.245	0.079	0.184	0.053	0.077	0.053	0.086	0.620
Smart sensors & robotics	0.164	0.070	0.138	0.038	0.103	0.084	0.035	0.297
V+	0.245	0.079	0.138	0.053	0.103			
V-	0.164	0.071	0.161	0.046	0.077			

Table 4.12: Normalized decision matrix for expert 2

The normalized decision matrix, optimum solution, negative optimum solution, the estimated distance between each alternative from the optimum best, the estimated distance each alternative from the optimum worst, performance rating and the final ranking for the third expert, which is shown in Table 4.13. At first observation, it can be seen cyber physical system has a higher estimated distance value between each alternative from the optimum best than the estimated distance between each alternative from the worst optimum solution, hence it has a low performance score and it is ranked the second most preferred alternative with a score closer to the third alternative but a higher score. Cloud computing has a really low estimated distance value between each alternative from the optimum best and a higher estimated distance between each alternative from the worst optimum solution, hence it results in the highest performance score among the other alternatives and it is ranked the first preferred alternative. Smart sensors and robotics have a high estimated distance value between each alternative from the optimum best and a low estimated distance between each alternative from the worst optimum solution, which results in a low performance score and it ranked third which is the least preferred alternative.

	Cost	Technological capability	Sustainability	Resource consumption	Quality	S+	S-	Ranking score
Cyber-physical system	0.160	0.083	0.169	0.028	0.090	0.132	0.034	0.203
Cloud computing	0.288	0.062	0.145	0.062	0.079	0.034	0.133	0.797
Smart sensors & robotics	0.160	0.073	0.169	0.042	0.090	0.130	0.032	0.196
V+	0.288	0.083	0.169	0.062	0.090			
V-	0.160	0.062	0.145	0.028	0.079			

Table 4.13: Normalized decision matrix for expert 3

4.3. Aggregating AHP and TOPSIS results

The final results of all the three experts criteria for AHP method and the aggregate of all expert results, which is displayed in Table 4.14. The aggregate was derived by finding the average of all three expert results. At first view, it can be observed that after the final average of all expert opinion cost is the most important criteria, then sustainability comes second with no huge difference, followed by technological capability, followed by quality and then finally resource consumption which is the least important criteria amongst the five criteria. It can also be observed that for the first and third expert cost was the highest scored criteria, however for the second expert sustainability was the highest scored criteria.

	Expert 1	Expert 2	Expert 3	W_{ci} =1/3 $\sum_j W_{cij}$
Cost	0.45	0.29	0.36	0.367
Technological capability	0.13	0.05	0.2	0.127
Sustainability	0.28	0.47	0.09	0.28
Resource consomption	0.05	0.09	0.1	0.08
Quality	0.09	0.1	0.26	0.15

Table 4.14: Aggregated AHP results of all experts

The combined TOPSIS results of all three experts and the final ranks of all alternatives is shown in Table 4.15 below. At an initial glance it can observed that the first expert ranked cyber-physical systems was first followed by big data & cloud computing which was ranked second however it was relatively small in comparison to cyber-physical system and smart sensors & robotics was ranked third with a very small score. The second expert ranked big data & cloud computing first followed closely by cyber-physical systems which was ranked second and smart sensors was ranked third with a small score. The third expert ranked big data & cloud computing first with a high score, followed by cyber-physical systems which was ranked second with a low score and smart sensors and robotics was ranked third with a very similar score to cyber-physical system. Overall, the average of all experts shows that big data & cloud computing was the most preferred alternative in this research, cyber physical system was ranked second with a close score to the first ranked and smart sensor & robotics was ranked third which is the least preferred alternative.

	Expert 1	Expert 2	Expert 3	$W_{ak} = 1/3 \sum_j W_{akj}$	Rank
Cyber-physical systems	0.943	0.545	0.203	0.564	2
Big data & Cloud computing	0.386	0.620	0.797	0.601	1
Smart sensors & Robotics	0.070	0.297	0.196	0.188	3

Table 4.15: Combined TOPSIS result of all experts

4.4. Analyzing the results

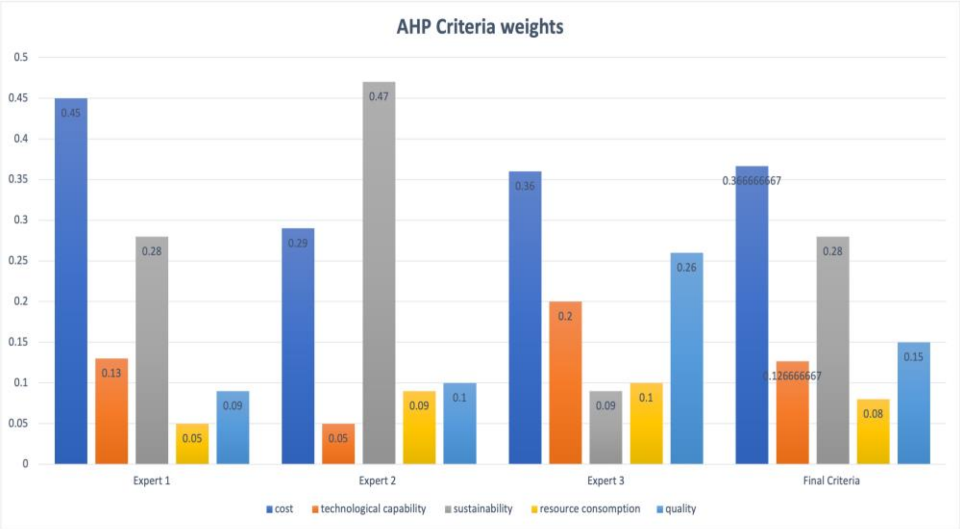

Figure 4.1: AHP criteria weights

The aggregated criteria of all experts on a chart, which is displayed in figure 4.1 and it makes it easy to understand each expert opinion on each different criteria. It indicates that cost is the most important criteria whereas sustainability is also very important and the least important criteria is resource consumption.

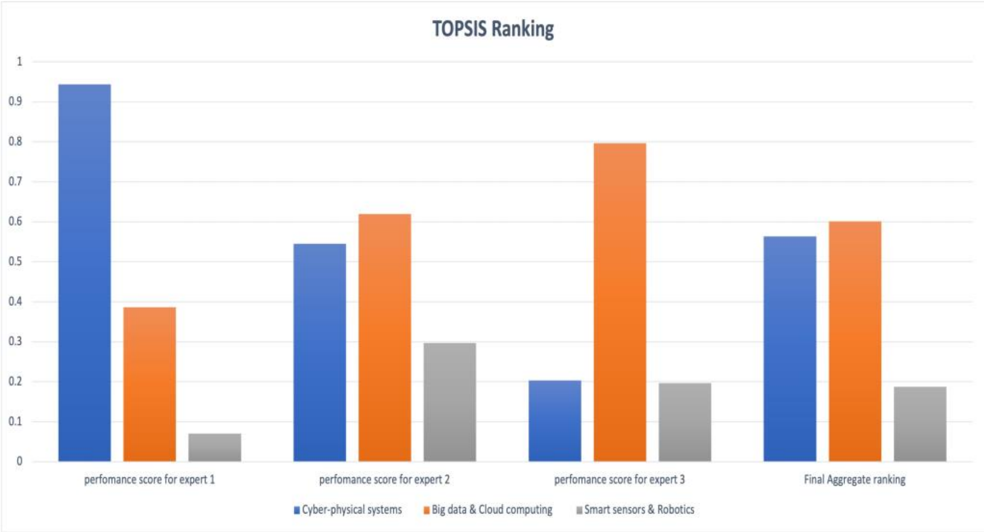

Figure 4.2: TOPSIS ranking

The ranking of the three experts and the final aggregate ranking is displayed in figure 4.2. it can be observed from the chart that big data & cloud computing are the most preferred alternative, followed by the cyber-physical systems which comes close in performance score to cyber-physical system but it is second in ranking and finally the least preferred alternative is smart sensors & robotics.

5. DISCUSSIONS

The present paper contributes an extensive and organized way of implementing industry 4.0 applications successfully in Nigerian Agricultural sector. The first objective of this study was to develop more knowledge, evaluate and make comparisons within the different activities of industry 4.0 applications in the agricultural sector of Nigeria. In order to realize the first objective, the study investigated the current literature to identify five important criteria affecting the successful implementation of industry 4.0 in agriculture and evaluate them by experts. The study recommended five criteria which were critical for the successful implementation of agriculture 4.0 in Nigeria, namely, cost, technological capability, sustainability, resource consumption and quality.

The second objective of the study was to aid decision makers in identifying the most suitable alternative depending on each problem encountered in agriculture 4.0 in Nigeria. Hence an integrated AHP and TOPSIS approach was used to prioritize the criteria with numerical weights and TOPSIS was used to rank the alternatives preferred for industry 4.0 applications in Nigeria.

Big data and Cloud computing were ranked first and found to be the most suitable alternative. The implementation of cloud computing in agriculture has created the necessary developments for agricultural productions, marketing, distribution of agro products and sales all over the world. Low cost access to IT resources has also been a significant advantage of Big data and Cloud computing (Goraya & Kaur, 2015). Big data can be used to enable certain resource applications such as fertilizers which ultimately increases productivity and reduce cost. It can also be used to ensure management of farming processes, farm management and accurate decision making. It can easily be implemented in Nigeria. Cyber-physical systems were ranked second in alternatives and the performance score was really close to the first ranked. They can create a modern and precise infrastructure in agricultural sector, food security may be achieved through the implementation of this technology and data about soil, climate and pest can be easily collected for precision agriculture. The least preferred alternative was smart sensors and robotics which is because it would be the most expensive alternative, consumes the most resources for implementation in Nigeria and may even lead to less human labor. However, Agricultural robotics is an optimistic solution for handling the issues in agricultural sector because tasks can easily be executed more efficiently and uniformly with accuracy. Weed spraying and pesticide control are more accurately carried out by agricultural field robots. Furthermore, fields can be scouted, data can be easily collected and harvesting can also be executed efficiently by agricultural robots and smart sensors. Implementation of robotics in Nigeria will be difficult but can still be achieved.

Two of the experts are males from Nigeria who are experienced in the agriculture sector and the third expert is a female from turkey and she is an expert in supply chain management. The results are fairly accurate in reality because Nigeria is an under developed country and cost is a major factor in success and implementation of any new technology in Nigeria.

6. CONCLUSION

Technology advancements in agricultural sector significantly influences every country's economy positively. The Agricultural industry in Nigeria needs a sustainable alternative to tackle hunger, food wastage, well organized supply chain network, improved productivity in the country and create more job opportunities. Implementations of the industry 4.0 applications in the agricultural sector may improve the current state of the Nigerian economy and help curb hunger, food wastage and even increase productivity. Agriculture is one of the sectors that has benefitted massively from industry 4.0 applications all over the world.

In this thesis, MCDM methods such as AHP and TOPSIS method were combined to select the most suitable industry 4.0 applications of Agriculture in Nigeria. In our methodology a group of experts were selected and queried to provide values for decision matrix of pairwise comparison and also for ranking of alternatives in TOPSIS. This research was carried out because new efficient methods are required to tackle, hunger, food wastage and supply chain problems in the food network. it may provide a new sustainable means of productivity, alternative modern methods, reduce food wastage and hunger in the country and it is the first-time industry 4.0 applications using MCDM approaches are being applied in agricultural sector of Nigeria. Big data & cloud computing were found to be most suitable alternative, cyber-physical system was ranked second and the least preferred alternative was smart sensors and robotics for industry 4.0 applications in Nigeria.

Future research may be carried out because even after detailed literature review was performed, however it is not possible to ascertain that there are no other important criteria because there may be various key criteria and alternatives that may not have been discussed in the currently available literature. Thus, the rating of criteria weights and ranking of alternatives may be different if new criteria and alternatives are added or existing criteria or alternative is removed. Analysis of such criteria or alternatives can be the subject of future studies. In addition, this study does not focus on the implementation of industry 4.0 on supply chain network of Nigerian agricultural sector, which can also be a subject of future research. Furthermore, the results of this study may be compared to other MCDM methods.

BIBLIOGRAPHY

Accenture (2020). Digital agriculture: improving profitability. Retrieved from https://www.accenture.com/us-en/insights/interactive/agriculture-solutions

Ardielli, E. (2019). Use of TOPSIS method for assessing of Good Governance in European Union Countries. *Review of Economic Perspectives*, vol. 19, pp. 211-231.

Arif-Uz-Zaman, K. & Ahsan, N. (2014). Lean supply chain performance measurement. *International Journal of Productivity and Performance Management*, vol.63(5), pp. 588-612.

Akses, A. (2021). Week 4: Industrial Revolutions [lecture slides]. Retrieved from https://bbbscalecls1.iku.edu.tr/playback/presentation/2.0/playback.html?meetingId=64c6a9c1fbe18b62e8c661f51a094869f0ac28c7-1616076004282

Aytekin, A., Ayaz, A. & Tumincin, F. (2019). Intelligent and natural agriculture with industry 4.0. *Journal of Bartin Faculty of Forestry*, Vol. *2*1, No.3. pp. 938-944. DOI: 10.24011/barofd.577714

Bigliardi, B., Bottani, E., Casella, G. (2020). Enabling technologies, application areas and impact of industry 4.0: A bibliographic analysis. *Procedia Manufacturing*, vol.42. pp.322-326. Retrieved from DOI:10.1016/j.promfg.2020.02.086

Brans, J.P. and Vincke, P. (1985) A Preference Ranking Organization Method: (The PROMETHEE Method for Multiple Criteria. Decision-Making). Management Science, 31, 647-656. Retrieved from http://dx.doi.org/10.1287/mnsc.31.6.647

Braun, A., Colangelo, E. & Steckel, T. (2018). Farming in the Era of Industry 4.0. *Procedia CIRP*. vol.72. pp. 979-984.

Bukhsh, A., Z., Stipanovic, I., & Doree, G., A. (2020). Multi-year maintenance planning framework using multi-attribute utility theory and genetic algorithms.

Calik, A. (2021). A novel Pythagorean fuzzy AHP and fuzzy TOPSIS methodology for green supplier selection in the industry 4.0 era.

Channe, H., Kothari, S., Kadam, D. (2015). Multidisciplinary Model for Smart Agriculture using Internet of Things(IoT), Sensors, Cloud-Computing, Mobile-computing & Big Data Analysis. *International journal of Computer Technology & Applications. Vol.6,(3)*, pp. 374-382.

Claudine, S., Raja, K. (2018). Scope for Industry 4.0 in the Agri-food Supply Chain. *Epubli*. Retrieved from http://tubdok.tub.tuhh.de/handle/11420/1787

Colapinto, C., Jayaraman, R., & Marsiglio, S. (2015). Multi-criteria decision analysis with goal programming in engineering, management and social sciences: a state-of-the art review.

Devi, K., & Yadav, S., P. (2013). A multicriteria intuitionistic fuzzy group decision making for plant location selection with ELECTRE method. *The International Journal of Advanced Manufacturing Technology* 66, pp.1219- 1229.

Emovon, I. & Oghenenyerovwho, O. (2020). Application of MCDM method in material selectin for optimal design: A review. Retrieved from https://doi.org/10.1016/j.rinma.2020.100115

The Food and United Organization of the United Nations (2019). Digital technology in agriculture and rural areas: Briefing paper. *Food and Agriculture Organization of the United Nations:* Rome. Retrieved from http://www.fao.org/3/ca4887en/ca4887en.pdf

Farming First (2021). Innovations for Sustainable Food Systems. Retrieved from https://farmingfirst.org/sustainable-food-system/section-3-supply-chain/#home

Fresco, R., Ferrarri, G. (2018). Enhancing precision agriculture by Internet of Things and cyber physical systems. Retrieved from http://www.tlc.unipr.it/ferrari/Publications/Journals/FrFe_AST18.pdf

Galati, F., & Bigliardi, B. (2019). Industry 4.0: Emerging themes and future research avenues using a text mining approach. Vol.109. pp.100-113. Retrieved from https://doi.org/10.1016/j.compind.2019.04.018

Ghosh, A., & Kar, K., S. (2018). Application of analytical hierarchy process (AHP) for flood risk assessment: a case study in Malda district of west Bengal, India.

Golfam, P., Ashofteh, P., S., Rajaee, T., & Chu, X. (2019). Prioritization of Water Allocation for Adaptation to Climate Change Using Multi-Criteria Decision Making (MCDM).

Goraya, M., S. & Kaur, H. (2015). Cloud Computing in Agriculture. *Open international journal of Technology Innovations and Research.* Vol.16.

Ic, Y., T. (2020). A multi-objective credit evaluation model using MOORA method and goal programming. *Arabian journal for Science and Engineering*, vol. 45, pp. 2035-2048.

Indahingwati, A., Wajdi, M., B., Susilo, D., E., Kurniasih, N & Rahim, R. (2018). Comparison Analysis of TOPSIS and Fuzzy Logic Methods On Fertilizer Selection. *International Journal of Engineering & Technology*, vol 7, pp 109-114.

Klerkx, L., Jakku, E. & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS-Wageningen Journal of Life Sciences*. Vol.90, pp.100315. Retrieved from https://doi.org/10.1016/j.njas.2019.100315

Kovacs, I. & Husti, I. (2018). The role of digitization in the agricultural 4.0 – how to connect the industry 4.0 to agriculture ?. *Hungarian agricultural engineering*. pp.38-42. Retrieved from http://dx.doi.org/10.17676/HAE.2018.33.38

Lee, J., Park, G., I., Shin, J., H., Lee, J., H., Sreenan, C., J. and Yoo, S., E. (2018). SoEasy: A software framework for easy hardware control programming for diverse IoT platforms. *Sensors*. Vol. 18, pp.7.

Lezoche, M., Hernandez, J., E., Alemany, M., M., E. & Panetto, H. (2020). Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture. *Computers in Industry*. Retrieved from http://dx.doi.org/10.1016/j.compind.2020.103187

Mardani, A., Jusoh, A., Nor, K., M., Khalifah, Z., Zakwan, N. & Valipour, A. (2015). Multiple criteria decision-making techniques and their applications: a review of the literature from 2000-2014. *Economic Research-Ekonomska*

Istraživanja, vol.28, no.1, pp.516-571, Retrieved from https://doi.org/10.1080/1331677X.2015.1075139

Mastrocinque, E., Ramirez, F., J., Escribano, A., H. & Pham, D., T. (2020). An AHP based multi-criteria model for sustainable supply chain development in the renewable energy sector. *Expert Systems with Applications.* Vol. 150, pp.113321. Retrieved from

https://doi.org/10.1016/j.eswa.2020.113321

Mateo, C.,S.,R.,J. (2012). Multi-Attribute Utility Theory. *Multi Criteria Analysis in the Renewable Energy Industry*, pp 63-72.

Miah, S., J., Ahsen, K. & Msimangira, K., A.B. (2013). An Approach of Purchasing Decision Support in Healthcare Supply Chain Management. *Operations and Supply Chain Management.* Vol.6, no.2, pp.43-53.

Mazumder, S., Kabir, G., Hasin, M. & Ali, S.M. (2018). Productivity Benchmarking Using Analytic Network Process (ANP) and Data Envelopment Analysis (DEA). *Big Data & Cognitive Computing*, Vol.*2*, issue 3, pp.27.

Mendas, A., & Delali, A. (2012). Integration of Multi Criteria Decision Analysis in GIS to develop land suitability for agriculture: application to durum wheat cultivation in the region of Mleta in Algeria. *Computers and Electronics in Agriculture*, pp. 117-126.

Miranda, J., Ponce, P., Molina, A. & Wright, P. (2019). Sensing, smart and sustainable technologies for agri-food 4.0. *Computer Industries* . Vol.108, pp. 21–36. Retrieved from https://doi.org/10.1016/j.compind.2019.02.002

Mocnej, J., Seah, W., Pekar, A. and Zolotova, I. (2018). Decentralized IoT architecture for efficient resources utilization. *Ifac Papersonline*, Vol. 51, no.6, pp. 168-173.

Mosconi, F. (2015). The new European industrial policy: Global competitiveness and the manufacturing renaissance. London, England: Routledge. Retrieved from https://doi.org/10.4324/9781315761756

Mustafa, A., A., Singh, M., Sahoo, R., N., Ahmed, N., Khanna, M., Sarangi, A. & Mishra, A.,K. (2011). Land suitability analysis for different crops: a multi criteria decision making approach using remote sensing and GIS. *Researcher*. vol.3, issue12 , pp. 61-84.

National Institute of Standards and Technology (NIST), (2017). CPS PWG Cyber-Physical Systems (CPS) Framework Release 1.0. Retrieved from https://pages.nist.gov/cpspwg/

Ozcan, E., C., Unlusoy, S., Eren, T. (2017). A combined goal programming – AHP approach supported with TOPSIS for maintenance strategy selection in hydroelectric power plants. *Renewable and Sustainable Energy Reviews.* Vol.78. pp.1410-1423. Retrieved from

http://dx.doi.org/10.1016/j.rser.2017.04.039

Ozdogan, B., Gacar, A. & Aktas, H. (2017). Digital agricultural practices in the context of agriculture 4.0. *Journal of Economics, Finance and Accounting (JEFA).* Vol.4, Iss.2, pp. 184-191. Retrieved from http://doi.org/10.17261/Pressacademia.2017.448

Palcic, I., & Lalic, B. (2009). Analytical Hierarchy Process As A Tool For Selecting And Evaluating Projects.

Papathanasiou, J., Ploskas, N. (2018). TOPSIS: Multiple Criteria Decision Aid. *Springer Optimization and Its Applications*. Vol.136, pp.1-30. Retrieved from https://doi.org/10.1007/978-3-319-91648-4_1

Qiu, X., Luo, H., Xu, G., Zhong, R. and Huang, G.,Q. (2015). Physical assets and service sharing for IoT-enable Supply Hub in Industrial Park (SHIP). *International journal of Production Economics*, vol.159, pp. 4-15.

Roblek, V., Mesko, M. & Krapez, A. (2016). A Complex View Of Industry 4.0. *Sage Journals*. Vol.6, issue 2. Retrieved from https://doi.org/10.1177/2158244016653987

Rose, D. C. & Chilvers, J. (2018). Agriculture 4.0: Broadening Responsible Innovation in an Era of Smart Farming. *Journal of Frontiers in Sustainable Food Systems, vol.2, pp.87*. doi: 10.3389/fsufs.2018.00087

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International Journal of Services Sciences*, vol.1, No.1, pp.83–98.

Sadiku, M., N., O., Ashaolu, T., J., & Musa, S., M. (2020). Big Data in Agriculture. *International journal of scientific advances,* vol.1. retrieved from www.ijscia.com

Santonja, G., G., Calvo, V., V., & Lepe, G., C. (2019). Application of AHP and corrective factors for the determination of best available techniques and emission limit values at installation level: A case study in four cement installations. Retrieved from https://doi.org/10.1016/j.scitotenv.2018.12.473

Schniederjans, G., D., Curado, C. & Khalajhedayati, M. (2020). Supply chain digitization trends: An integration of knowledge management. *International Journal of Production Economics.* Retrieved from https://doi.org/10.1016/j.ijpe.2019.07.012

Sitorus, F., Cilliers, J., J., Brito-parada, R. (2019). Multi-criteria decision making for the choice problem in mining and mineral processing: Applications and trends. *Expert systems with applications.* vol. 121. pp.393-417

Shi, G. & Wang, Q. (2019). The Application of Utility Theory in Decision Making of Marketing Risk Management.

Ślusarczyk, B.(2018). Industry 4.0-Are we ready? *Polish Journal of Management Studies*, 17(1),pp 232-248. Retrieved from DOI : 10.17512 / pjms.2018.17.1.19

Songur, N., H. (2018). Application of Analytical Hierarchy Process Method in Database Tool Selection. (Doctoral dissertation, Institute of Science and Technology, Beykent University).

Soosay, C. & Kannusamy, R. (2018). Scope for industry 4.0 in the agri-food supply chain. Retrieved from

http://hdl.handle.net/10419/209342

Spanaki, K., Sivarajah, U., Fakhimi, M., Despoudi, S., & Irani, Z. (2021). Disruptive technologies in agricultural operations: A systematic review of AI-driven AgriTech research. Annals of Operations Research. https://doi.org/10.1007/s10479-020-03922-z

Srisawat, C. & Payakpate, J. (2016). Comparison of MCDM methods for intercrop selection in rubber plantations. *Journal of ICT*, no 1, pp: 165-182.

Stankovic, M., Gladovic, P., & Popovic, V. (2019) Determining the importance of the criteria of traffic accessibility using fuzzy AHP and rough AHP method. *Decision Making: Application in Management and Engineering*, no 2, pp:86-104.

Trienekens, J., H., Wognum, P., M., Beulens, M., J., & Vorst, J., A. (2012). Advanced engineering informatics. Vol.26, pp.55.

Thomas, A. & Trentesaux, D. (2013). Are intelligent manufacturing systems sustainable?. 3rd workshop on service orientation in holonic and multi agent manufacturing and robotics, SOHOMA, *AGIR Publishing House*, pp. 105-114.

Ullo, L., S., & Sinha, G., R. (2021). Advances in IoT and Smart Sensors for Remote Sensing and Agriculture Applications. Vol.13, (13), pp 2585. Retrieved from **https://doi.org/10.3390/rs13132585**

Velasquez, M. & Hester, T., P. (2013). An analysis of multi-criteria decision making methods. *International journal of operations research.* Vol. 10, No. 2, pp 56 - 66.

Vougioukas, S.G. (2019). Agricultural Robotics. Retrieved from https://doi.org/10.1146/annurev-control-053018-023617

Wang, T. (2012). The interactive trade decision making research: An application case of novel hybrid MCDM model. *Economic modelling.* Vol. 29, no.3, pp 926-935. Retrieved from https://doi.org/10.1016/j.econmod.2012.02.001

Weltzien, C. (2016). Digital Agriculture or why agriculture 4.0 still offers only modest returns. *Landtechnik.* Vol.71, pp. 66-68.

Yahya, N. (2018). Agricultural 4.0: Its Implementation Toward Future Sustainability. *Green energy and technology.* pp. 125–145. Retrieved from https://doi.org/10.1007/978-981-10-7578-0_5

Yanie, A., Hasibuan, A., Ishak, I., Marsono, M., Lubis, S., Nurmalini, N., Mesran, M., Nasution, D., S., Rahim, R., Nurdiyanto, H. & Ahmar, S., A. (2018). Web Based Application for Decision Support System with ELECTRE method. *Journal of Physic Conference Series.* Vol.1028, Retrieved from https://doi.org/10.1088/1742-6596/1028/1/012054

Yucel, G.,M & Gorener, A. (2016). Decision Making for Company Acquisition by ELECTRE Method. *International journal of supply chain management.* Vol.5, pp. 75.

Zambon, I., Cecchini, M., Egidi G., Saporito ,G.,M. & Colantoni, A. (2019). Revolution 4.0: Industry vs agriculture in a future Development for SMEs. *Processes Journal*. Vol.7 pp.36. Retrieved from https://doi.org/10.3390/pr7010036

Zezulka, F., Marcon, p., Vesely, I. & Sajdi, O. (2016). Industry 4.0- An introduction in the phenomenom. *IFAC Papers Online* , Vol.49, issue 25, pp. 8-12.

https://doi.org/10.1016/j.ifacol.2016.12.002

Zecca, F. and Rastorgueva, N. (2014). Supply chain management and sustainability in agri-food system: Italian evidence. *Journal of Nutritional Ecology and Food Research,* Vol. 2, pp. 20-28.

Zhai, Z., Martinez, F.,J., Martinez, Beltran, V. & Martinez, L., N. (2020). Decision Support Sytems for agriculture 4.0 : Survey and challenges .*Computers and Electronics in Agrculuture*. Vol 170. Retrieved from https://doi.org/10.1016/j.compag.2020.105256

Zhang, Y. & Chang, C. (2020). Modelling the US-China trade conflict: a utility theory approach.

APPENDIX A_

Table A.1 Normalized pairwise matrix and criteria weights for expert 1

Criteria	Cost	Technological capability	Sustainability	Resource consumption	Quality	Criteria weights
Cost	0.48	0.45	0.52	0.39	0.43	0.45
Technological capability	0.12	0.11	0.09	0.17	0.17	0.13
Sustainability	0.24	0.34	0.26	0.28	0.26	0.28
Resource consumption	0.07	0.04	0.05	0.06	0.04	0.05
Quality	0.10	0.06	0.09	0.11	0.09	0.09

Table A.2 Normalized pairwise matrix and criteria weights for expert 2

Criteria	Cost	Technological capability	Sustainability	Resource consumption	Quality	Criteria weights
Cost	0.22	0.316	0.178	0.324	0.417	0.29
Technological capability	0.04	0.053	0.076	0.027	0.042	0.05
Sustainability	0.65	0.368	0.533	0.405	0.417	0.47
Resource consumption	0.06	0.158	0.107	0.081	0.042	0.09
Quality	0.04	0.105	0.107	0.162	0.083	0.10

Table A.3 Normalized pairwise matrix and criteria weights for expert 3

Criteria	Cost	Technological capability	Sustainability	Resource consumption	Quality	Criteria weights
Cost	0.35	0.51	0.27	0.4	0.267	0.36
Technological capability	0.12	0.17	0.27	0.16	0.267	0.20
Sustainability	0.12	0.057	0.091	0.04	0.133	0.09
Resource consumption	0.070	0.09	0.182	0.08	0.067	0.10
Quality	0.35	0.17	0.182	0.32	0.267	0.26