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Implementation of an Intelligent Model Based on Big Data and Decision Making Using Fuzzy Logic Type-2 for the Car Assembly Industry in an Industrial Estate in Northern Mexico

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Abstract. In our days, we are living the epitome of Industry 4.0, where each component is intelligent and suitable for Smart Manufacturing users, which is why the specific use of Big Data is proposed to determine the continuous improvement of the competitiveness of a car assembling industry. The Boston Consulting Group (Rüßmann et al., 2015) has identified nine pillars of I4.0, which are: (i) Big Data and Analytics, (ii) Autonomous Robots, (iii) Simulation, (iv) Vertical and Horizontal Integration of Systems, (v) Industrial Internet of Things (IoT for its acronym in English), (vi) Cybersecurity, (vii) Cloud or Cloud, (viii) Additive Manufacturing including 3D printing, and (ix) Augmented Reality. These pillars can all be implemented in factories or take some depending on the case you want to improve. In Industry 4.0, the Industrial IoT is a fundamental component and its penetration in the market is growing. Car manufacturers such as General Motors or Ford expect that by 2020 there will be 50 billion (trillion in English) of connected devices (Khan & Salah, 2018) and Ericsson Inc. estimates 18 billion (Scott, 2018). These estimated quantities of connected devices will be due to the increase in technological development, development in telecommunications and adoption of digital devices, and this will invariably lead to the increase in the generation of data and digital transactions, which leads to the mandatory increase in regulations, for security, privacy and informed consent in the integration of these diverse entities that will be connected and interacting among themselves and with the users. Finally, the use of Fuzzy Logic type 2 is proposed to adapt the correct decision making and achieve the reduction of uncertainty in the car assembly industry in the Northeast of Mexico.

Keywords: Smart manufacturing, industrial IoT, big data applied to the automotive industry, fuzzy logic type 2 for decision makings.

1 Introduction

This document makes a literature review of the concepts of industry 4.0, big data, fuzzy logic type 2, also you will see an example of decision making based on the TOPSIS methodology implemented in MatLab that will be the basis for the proposal of this chapter.

2 Literature Review

This section shows the main concepts to this article and how they have been generating and evolving along the history, this section gives us an idea of what exists with respect to the technologies mentioned as Industry 4.0, Big Data, Fuzzy Logic Type-2.

2.1 Industry 4.0

Industry 4.0 (I4.0) is the latest standard for data and computation oriented advanced manufacturing [1], The term "Industry 4.0" originated from a project initiated by High-tech strategy of the German government to promote the computerization of manufacturing.

Industry 4.0 is considered as the next phase in the digitization of the manufacturing sector, and it is driven by four disruptions: the astonishing rise in data, computational power, and connectivity, especially new low-power wide-area networks [2], the I4.0 was named because in along the history it was the fourth industrial revolution, the first one (I1.0) refers to the first revolution which occurred in the 1800s, where the most important change was mechanical manufacturing, then in the 1900s take place the second revolution which have as main chance the assembly line and it means an increase in mass production, before the I4.0 occurs the third revolution, this happened around the 1970 when the industry introduce the use of robots get better in the production, all this information was taken from the next table.

As it mentions before the I4.0 is based on nine pillars this was written by [3] and they are:

1- Big Data and Analytics

2- Autonomous Robots

3- Simulation

4- Horizontal and Vertical System Integration

5- The Industrial Internet of Things

6- Cybersecurity

7- The Cloud

8- Additive Manufacturing

9- Augmented Reality

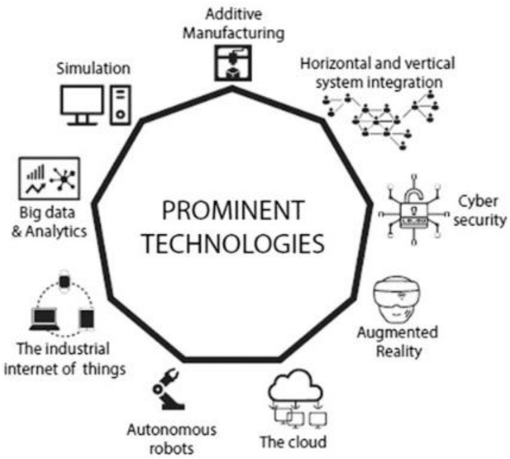

Fig. 1. Group technologies in Industry 4.0 [4].

Table 1. Technology evolution from Industry 1.0 to Industry 4.0. [1]

Time	Evolution Transition	Defining technology
1800s	Industry 1.0	Mechanical Manufacturing
1900s	Industry 2.0	Assembly Line (mass production)
1970	Industry 3.0	Robotic Manufacturing (Flexible Manufacturing)
2010	Industry 3.5	Cyber Physical Systems
2012 Foward	Industry 4.0	Virtual Manufacturing

This emerging concept of Industry 4.0 is an umbrella term for a new industrial paradigm that encompasses a range of future industrial developments in relation to Cyberphysical Systems (CPS), the Internet of Things (IoT), the Internet of Services (IoS), Robotics, Big Data, Cloud Manufacturing and Augmented Reality.

The adoption of these technologies is fundamental for the development of more intelligent manufacturing processes, which include devices, machines, production modules and products capable of exchanging information independently, triggering actions and controlling each other, enabling an intelligent manufacturing environment [5].

The term industry 4.0 has been used throughout the world, both academically and in industry, although this term has been handled in different ways, for example in China the term "Made-in-China 2025" was introduced, in the United States of America it is called "Re-industrialization", in Japan they refer to the "New Robotics Strategy" to methods that allow manufacturing fully customized products with the help of integrating the entire supply chain and production system [6].

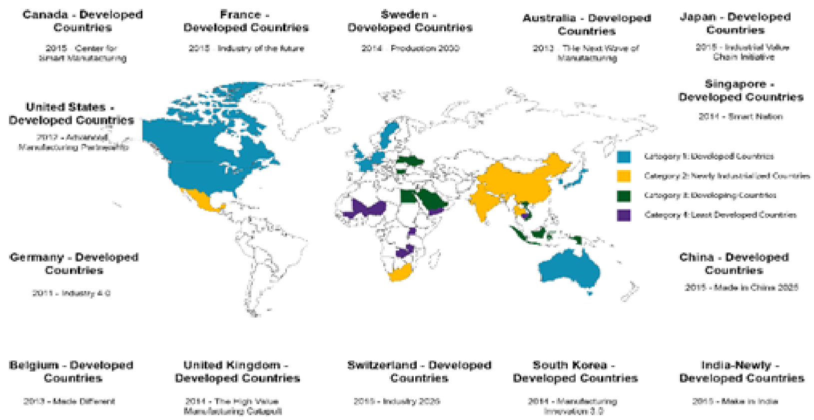

Fig. 2. Industry 4.0 initiatives around the world [7].

Intelligent supply chains will be highly automated and integrated and, again, made possible through the integration of software and communications in the industry, CPS generates real-time data on their position and status, which allows to automate processes in the supply chain and identify products throughout the production process allowing manufacturers to identify changes in orders, in addition, allows to recognize inefficiencies, increase reliability and reduce costs [4]

2.2 Big Data

One of the most important part of I4.0 is the Big Data and Analytics, normally is associated with the result of the use of internet, sensors, management systems, but big data isn't about a big group of data, is a model named "Model of 3v's", Volume, Velocity, Variety. [8] Then this model was increase with a new "Vs", variability [9] for the "Model 4v's",the next suggest for the "Model 5v's" was value, and along the time this model has been increasing to the las model named "3v2 Model" and is mentioned by [10], and he show us the next Venn Diagram:

Some of the authors like Zhang, Zhan, & Yu [11] talk about the use of Big Data in the industry of car, He proposes that the use of big data helps determine the characteristics that a user searches for in a car, in addition to predicting how sales will be in the coming months.

Otherwise, Kambatla, Kollias, Kumar, & Grama [12] talk about the future to big data, he gives us an idea of what the use of big data implies, from the type of hardware that is needed to apply this technology, be it the use of memory, the hierarchy of memory that this implies, to the types of network and systems distributed that allow the application of big data for companies.

On the other hand, Philip Chen & Zhang [13] mentions that in order to be competent the use of big data is a big part for innovation, competition and production for any

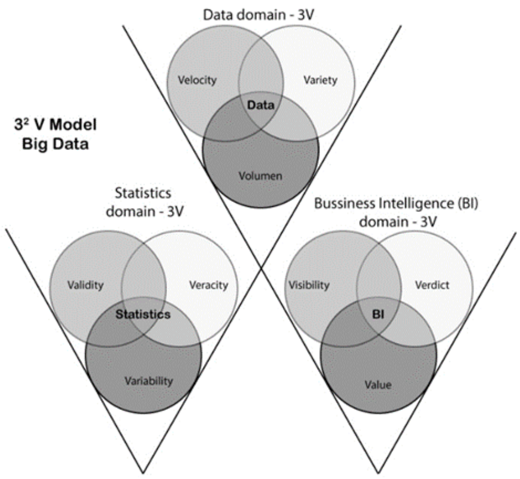

Fig. 3. 3^2Vs Venn diagrams in hierarchical model [10].

company, and that the use of big data should include the use of cloud computing. , quantum computation and biological computation, besides that the development of tools is an important part of the use of these technologies.

With the origin of new advances in technology, a huge amount of organized and unstructured data is delivered, collected from different sources such as social media, audios, websites, video among others, which makes the task of monitoring and processing such information difficult [14].

The decision making in a company is one of the biggest problems, the use of the techniques of the science of the data allows to take decisions in massive scale depending on the technologies of big data that is applied, in addition to the storage and the Engineering that the company is able to have, nevertheless, the processing of this information to scale continues being the privileges of a few with the capacity to integrate and to deploy the great tools of data processing [15].

The problem with any application begins at the point of storing its enormous, collected data. Therefore, there are some solutions that have come to light to solve the big problem of data storage. Below are some of the most famous tools already used in some of the applications and the table 2 summarizes the characteristics of data storage and management tools [16].

2.3 Fuzzy Logic Type-2

Type-2 fuzzy sets were originally proposed by Zadeh in 1975 and are essentially "fuzzy-fuzzy" sets in which the degrees of belonging are type-1 fuzzy sets [17].

Fuzzy algorithms have the common feature of not requiring a detailed mathematical model, the type 2 fuzzy logic system (FLS T2) can give robust adaptive response to a drive that has parameter variations, disturbance loading and non-linearity [18].

Table 2. Tools for the use of Big Data

Tool	Type	Platform
Cloudera	Hadoop distributed file system (HDFS)	Red Hat Enterprise (RHEL), CentOS, Ubuntu, Debian
Apache Cassandra	Database	Cross Platform
Chukwa	Hadoop distributed file system (HDFS)	Cross Platform
Apache Hbase	Hadoop distributed file system (HDFS)	Cross Platform
MongoDB	Document - orienteddatabase	Windows Vista and later, Linux, OS x 10.7 and later, Solaris, FreeBSD
Neo4j	Java - graphdatabase	Cross Platform
CouchDB	Erlang	Cross Platform
Terrastore		
HibariDB	Erlang - Key - value store	Cross Platform
Riak	NoSQL database, cloudstorage	Linux, BSD, macOS, Solaris
Hypertable	Associative array datastore / wide column store	Linux, Mac OS X
Blazegraph	Graph	Ubuntu
Hive	Data warehouse	Cross Platform
Infinispan	Data grid	Cross Platform

Fuzzy logic has obtained attention of researchers for last couple of decades. It has opened new horizons both in the academia and the industry site, although, conventional fuzzy systems (FSs) or so called type-1 FSs is capable of handling input uncertainties, it is not adequate to handle all types of uncertainties associated with knowledge-based systems[19], the type-2 provide additional design degrees of freedom fuzzy logic systems, which can be very useful when such systems are used in situations where lots of uncertainties are present, The resulting type-2 fuzzy logic systems (T2 FLS) have the potential to provide better performance than a type-1 (T1) FLS [20].

Even in the face of these difficulties, type 2 fuzzy logic has found applications in the classification of encoded video sequences, the elimination of co-channel interference from time-varying non-linear communication channels, connection admission control, knowledge extraction from questionnaire surveys, time series forecasting, function approximation, radiographic image pre-processing and transport scheduling [21].

A type-2 fuzzy set is characterized by a fuzzy membership function, i.e., the membership value (or membership grade) for each element of this set is a fuzzy set in [0,1], unlike a type-1 fuzzy set where the membership grade is a crisp number in [0,1] [22].

Membership functions of type-1 fuzzy sets are two-dimensional, whereas membership functions of type-2 fuzzy sets are three-dimensional. It is the new third-

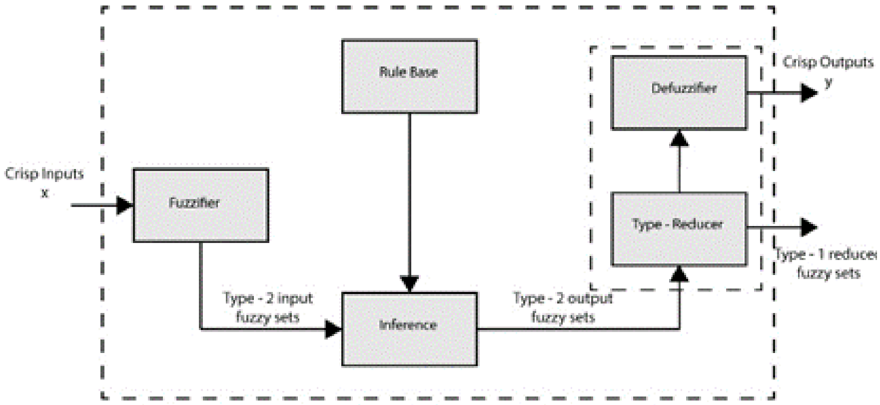

Fig. 4. Show us the diagram of a fuzzy logic controller.

dimension of type-2 fuzzy sets that provides additional degrees of freedom that make it possible to directly model uncertainties [20].

Nowadays the automotive industry uses different technologies with the purpose of increasing profits, this without stopping producing quality products, being these models of mathematical or stochastic type which have a great amount of uncertainty in them, which makes difficult the optimization of resources within the supply chain and decision making within the production of your product, starting from the fact that the use of these models results in a 60% in the optimization of resources within the industry.

On the other hand the use of Big Data analysis has been a fundamental tool for companies with a great number of variables and of great help in the decision making, besides the use of fuzzy logic type 2 and artificial intelligence also is part of the technologies of which the companies have at the moment to help, nevertheless the use of these combined technologies has not been proven and it is believed that the use of both technologies at the same time can give results of better way, that if they did it individually.

3 Analysis

This article proposes the analysis by means of the TOPSIS method of the recurrent problems in the automotive industry at the time of assembling the models of automobiles, considering the opinion of the participants in the assembly of these, being the experts in the area, the workers of the industry and the automobile assembly companies.

On the other hand, for this case, different critical points were taken in the assembly, from which each one of the managers gave a qualification to the different criteria, being in the following way, the experts in the automotive industry were the ones in charge of assigning a qualification to the selection of the piece, implementation of the design

Table 3. Weights of the Criteria's.

Evaluator	Criteria Name	Criteria	Weights
Expert	C1	Parts Selection in the Industry 4.0	0.02
	C2	Design pattern implementation	0.01
	C3	Designing Issues in Cutting	0.01
	C4	Precision in Cutting	0.4
	C5	Ability under mental fatigue	0.02
Worker	C6	Time to design the industrial process	0.3
	C7	Difficulty in following design rules	0.01
	C8	Difficulty to generate the required creativity	0.01
	C9	Difficulty to organize the pieces in the industrial process	0.01
	C10	Quality Control	0.07
Company	C11	Export Parts Specifications	0.03
	C12	Continuous Product Improvement	0.09
	C13	Prototyping identification in the assembly	0.02
		Sum of Weights	**1**

pattern, design of issues in the cut, cut precision and the ability to work under mental fatigue; On the other hand, the workers were in charge of qualifying the time to design the industrial process, difficulty to follow the design rules, difficulty to generate the required creativity, difficulty to organize the parts in the industrial process and quality control, finally, the company qualified the specifications of the parts for export, continuous improvement of the product, identification of the prototyping in the assembly.

The first step to begin the TOPSIS analysis is to determine the weight that each criterion has within the analysis which is as follows and is shown in table 3.

For this purpose, each of the criteria to be analyzed was assigned a certain weight by those involved, Table 4 shows the criteria, weights, and models of the cars to be analyzed.

4 Solution

Using the tables and the previous data, an analysis was carried out using the Matlab platform and the code developed by Dr. Sianaki [23], this code needs as requirements to start the decision making matrix, the weight of each of the criteria and the sign of these, to enter each of them is necessary to fill an excel file and Matlab reads them through a function called "inputdata.m", once executed the Matlab code "topsis.m", this program does the whole procedure, going through the normalization of the data, the distance the ideal alternative and the distance to the worst alternative, to give the result as a ranking.

Table 4. Weights of the Criterias.

	EVALUATED BY THE EXPERT					EVALUATED BY THE WORKER					EVALUATED BY THE COMPANY		
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
BMW 1 Series Coupe, Convertible 2013	5.88	2.11	3.67	3.63	3.24	1.76	1.96	1.56	5.36	6.34	5.19	5.1	5.15
Audi 100 Wagon, Sedan 1994	3.05	3.3	5.97	6.84	4.35	6.46	2.74	6.6	3.78	2.37	2.47	6.96	1.7
FIAT 124 Spider Convertible 2019	1.56	2.22	2.81	4.71	3.85	6.86	3.56	2.07	6.96	6.51	3.79	1.97	6.43
Ram 1500 Classic Crew Cab Pickup 2019	1.87	4.65	6.56	4.03	6.08	2.85	5.96	3.98	4.99	4.21	3.79	3.68	1.66
Ram 1500 Classic Regular Cab Pickup 2019	2.39	3.15	3.73	5.97	4.51	2.55	5.57	2.07	2.73	5.79	5.39	4.87	5.04
GMC 1500 Club Coupe Pickup 1999	1.83	1.17	5.25	6.22	2.96	4.05	5.45	4.9	3.43	1.57	5.29	4.11	6.11
Chevrolet 1500 Regular Cab Pickup 1992	6.68	1.8	5.81	2.95	6.44	4.7	3.01	1.25	3.09	5.82	5.28	5.33	6.85
Alfa Romeo 164 Sedan 1995	3.92	4.8	5.75	2.83	5.43	5.32	1.64	3.19	5.65	3.4	1.44	6.73	3.19
Mercedes-Benz 190 E Sedan 1993	6.05	3.38	1.28	4.4	3.08	6.55	3.73	6.22	4.77	5.46	1.09	3.52	7
BMW 2 Series Coupe, Convertible 2019	3.3	4.65	3.31	5.47	3.76	2.68	2.9	5.57	5.65	6.26	3.66	1.7	2.41
weights	0.02	0.01	0.01	0.4	0.02	0.3	0.01	0.01	0.01	0.07	0.03	0.09	0.02

Car model	CC	Ranking
BMW 1 Series Coupe, Convertible 2013	0.221688874	1
Audi 100 Wagon, Sedan 1994	0.831447482	10
FIAT 124 Spider Convertible 2019	0.728775996	9
Ram 1500 Classic Crew Cab Pickup 2019	0.257714838	2
Ram 1500 Classic Regular Cab Pickup 2019	0.354804638	4
GMC 1500 Club Coupe Pickup 1999	0.506037614	5
Chevrolet 1500 Regular Cab Pickup 1992	0.507758872	6
Alfa Romeo 164 Sedan 1995	0.563052035	7
Mercedes-Benz 190 E Sedan 1993	0.728153278	8
BMW 2 Series Coupe, Convertible 2019	0.313836664	3

5 Conclusion

Based on the criteria analyzed the car "BMW 1 Series Coupe, Convertible 2013", was the easiest in the assembly according to experts and the criteria analyzed, the "Ram 1500 Classic Crew Cab Pickup 2019" for its part was in second place, in last place was the "Audi 100 Wagon, Sedan 1994", These results were proven by other technologies which gave similar results to these, on the other hand it is important to mention that the methods are still mathematical models implemented in technological tools, so it is important to develop technological methodologies for decision making.

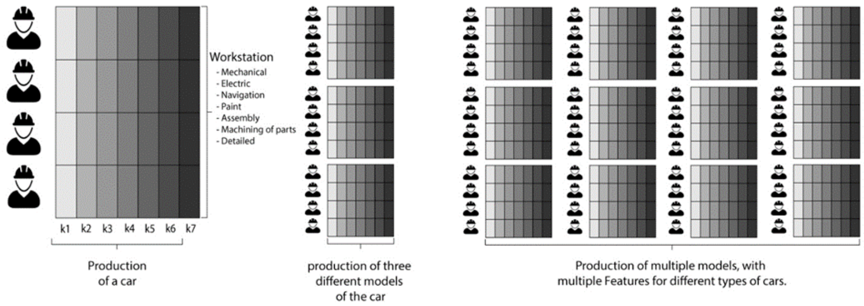

Fig. 5. A multiple production of cars with multiple variables produces multiple critical points within the company.

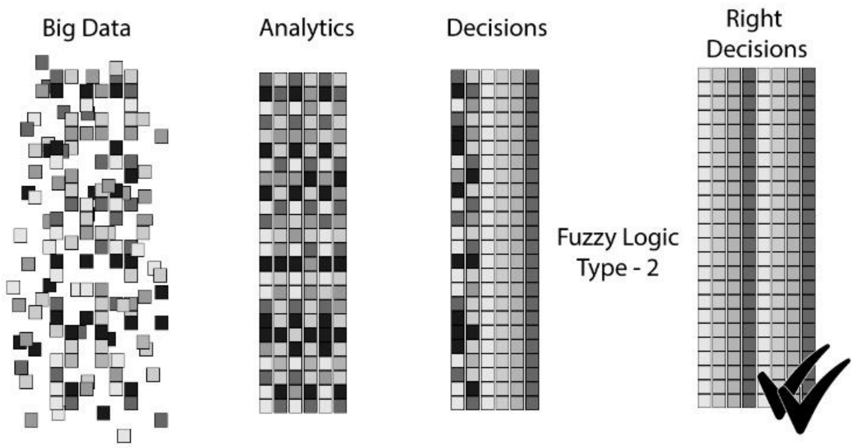

Fig. 6. Intelligent Methodology Proposed.

5.1 Research Proposal

Although these mathematical methods give us an idea of the behavior that a car manufacturer should have, these methods are not sufficient and although one can try to predict based on them there are always criteria that are not considered or worse to a not taken into account.

The automobile assembly industry today has multiple options for the assembly, from different models of cars, different types between these models, even the color of these is an important factor for decisions within companies.

Case, a car is assembling in 7 stages and this passes through 4 work stations, only the assembly of this car has as result 28 critical points, now if 3 different models are made at the same time, and what happens if 4 cars are made of each model, the number of variables and critical points of the process grow significantly as it can be seen in the figure, so the mathematical and stochastic models are not being practical enough for this type of companies. In figure 5 can be seen the multiple variables in the assembly of automobiles.

As can be seen in the assembly of multiple models of cars represents multiple variables, without counting the parts or external factors to the assembly process, which no longer give enough mathematical models, so we are working on a new intelligent methodology based on two computer tools such as Big Data and Type - 2 fuzzy logic, which will be able to support multiple quantitative and qualitative variables, which will be able to help in making decisions in real time.

The proposed intelligent methodology consists of two main parts, of which in the first part the Big Data technology will be able to generate improvement options through the analysis of large amounts of data, variables and values; on the other hand, the Type-2 Fuzzy Logic technology will analyze the options generated in the first part and considering the criteria out of the company's control, it will determine from the generated options the best option as shown in figure 6.

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