Multi-Criteria Decision-Making for Industry 4.0: A Comprehensive AHP (Analytic Hierarchy Process) Approach to Selecting IoT Devices, AI Models, and Simulation Tools in Automotive Manufacturing

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Abstract. The advent of Industry 4.0 has profoundly transformed industrial ecosystems through the integration of the Internet of Things (IoT), Artificial Intelligence (AI), and advanced simulation tools. In fact, production planning and internal logistics have been substantially enhanced due to these technologies. They have also enabled the transition to sustainable smart factories. However, choosing these technological alternatives remains a multifaceted challenge for manufacturers, due to the diversity and number of criteria to be considered, such as cost, performance, interoperability, scalability, and environmental impact. This paper provides both theoretical and practical contributions, through which we propose one of the most intersting multi-criteria decision-making (MCDM) methods, specifically the Analytic Hierarchy Process (AHP) method to help optimally select IoT devices, AI approaches and simulation software in the smart automotive factories context. The methodology establishes a hierarchy of criteria, namely investment costs, forecast accuracy, compatibility with existing systems, explainability, energy usage, and carbon footprint.

1 Introduction

The development of the industrial sector is essential for global economic growth, with the aim of providing society with better quality products at a lower cost and in a better time [1]. In the era of the fourth industrial revolution, technological advances such as the Internet of Things (IoT), machine learning (ML), and artificial intelligence (AI) have led to the emergence of intelligent manufacturing systems, also called smart factories, which aim to meet customer demand for product customization, price competitiveness, and reduced energy consumption. This evolution poses new challenges of flexibility in production, intelligently requiring cooperation between human workers, robots, and AI.

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The advancements in technologies like IIoT, big data and AI and the pervasive use of sensors in the factory have enabled the ability to monitor operations, conduct maintenance remotely, and manage production in real-time. Thus, factories can become more adaptive and self-optimizing, self-regulating, proactive, and able to manage constraints. [2].

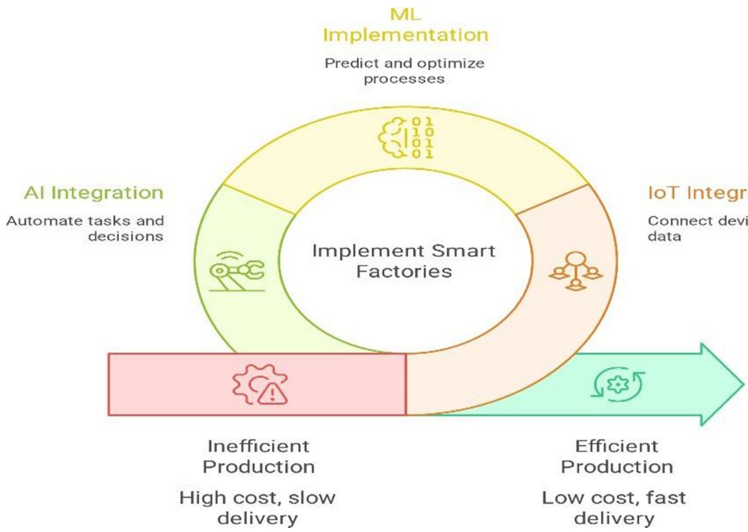

Fig. 1. Smart Factory

Indeed, IoT participates in the collection of real-time data to track equipment, manage logistics flows, and optimize energy resources [3], while AI, via machine learning and deep learning, allows for the analysis of this massive data to predict failures, optimize planning, and improve operational efficiency [4]. Finally, simulation software and digital twins are emerging as strategic tools for modeling production systems, anticipating logistics scenarios, and reducing energy consumption [5]. Different concrete applications in the automotive industry, which we take as a case study in this article, have made it possible to establish that the joint integration of IoT, AI, and simulation promotes the reduction of internal costs, the improvement of quality objectives, and the achievement of significant energy savings, as demonstrated by the results obtained with Tecnomatix Plant Simulation at Siemens [6].

In another study, shows that the use of Internet of Things (IoT) in supply chain management contributes to improving various performance metrics, such as flow speed, demand forecast accuracy, and cycle time reduction. Through automation and the analysis of data provided by connected devices, firms can increase their resilience and competition in the Industry 4.0 context. The advantage of IoT is therefore not confined to connectivity but becomes a strategic facilitator of sustainable performance.

This article presents some of these technologies that make the "smart factory" possible, namely the Internet of Things and AI. It presents the methods for choosing the technologies to adopt for each type of industry according to its constraints and environment. In order to make a better choice of these technologies, modeling is required [7]. We will focus on the choice method applied in the automotive industry, namely the AHP (Analytic Hierarchy Process) multi-criteria method [8]. But before that, we will give insights into IoT and AI technologies.

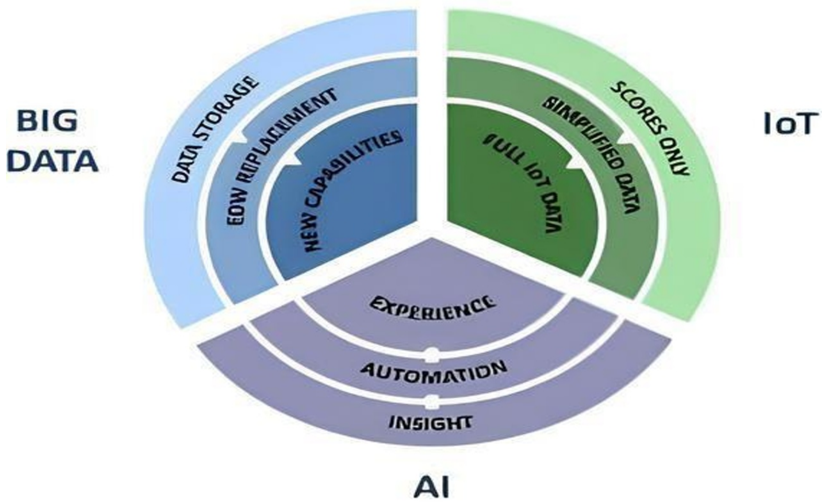

Fig. 2. The Integration of AI and Big Data for Digital Transformation

2 Concepts and Definitions

2.1 The Internet of Things (IoT) in Smart Factories

The Internet of Things (IoT) is no longer limited to a simple network of connected objects, but it is capable of managing a multitude of rapidly growing smart devices. Its deployment in smart factories constitutes one of its most revolutionary multi-sector applications [2].

Furthermore, the Industrial Internet of Things (IIoT) is currently transforming the global manufacturing sector by enabling the implementation of dynamic, efficient, and flexible infrastructures, followed by the interoperability of new connected applications for intelligent management of production systems and production data. The concrete benefits of the IIoT revolve around increased efficiency, lower operating costs, and better control of energy consumption. [9].

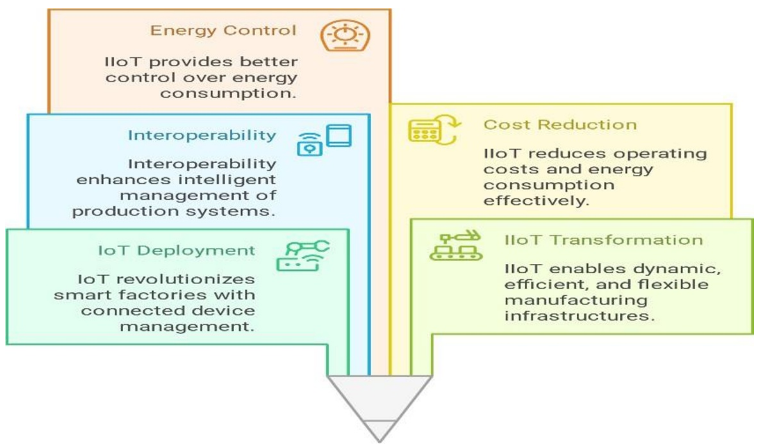

Fig. 3. IoT in Smart Factory of the Industry 4.0 System

2.2 AI in smart factories

Artificial intelligence is needed not only to automate tasks but also to enable machines to interact cognitively with humans and with each other. The end result of AI is the reproduction of human faculties such as problem-solving, decision-making, processing, and understanding natural language. On the other hand, industrial AI ensures that computers perform tasks historically performed by humans in production environments. It ensures daily exchanges between humans and machines through interactions with robots in smart factories [2].

AI contributes to greater efficiency in many industrial sectors, enabling advanced automation and process optimization. In fact, it not only reduces costs but also improves product quality, thanks to real-time monitoring and control systems [10]. With the integration of machine learning capabilities, machines adapt to changing working conditions and predict maintenance needs, increasing equipment durability [11]. As a result, AI plays a crucial role in the transition to more flexible and intelligent production environments.

More recently, emphasized the role of deep learning methods in demand forecasting within Supply Chain 4.0. The authors explain that by leveraging the massive data generated by IoT systems and digital platforms, neural network-based models allow for better anticipation of market needs and a reduction of uncertainties related to demand fluctuations. These intelligent approaches can improve decision making within organizations while enabling more sustainable practices related to production and logistics.

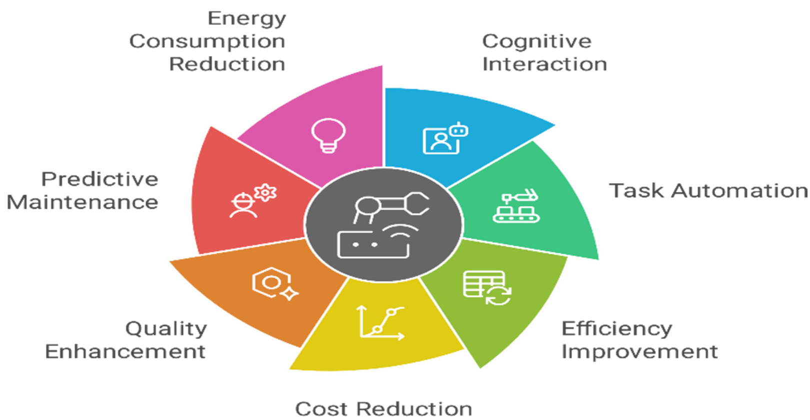

Fig. 4. AI in Industry 4.0

2.3 The Role of IoT and AI Integration in Enhancing Energy Efficiency in Smart Factories

2.3.1 The impact of IoT integration

In terms of sustainability in Industry 4.0, the Internet of Things (IoT) directly contributes to the optimization of energy consumption within industrial systems. Thanks to continuously deployed sensors, IoT devices enable real-time energy monitoring and reveal invisible areas of energy waste [12]. In addition, according to [13], the multi-layer architecture integrating sensors, edge computing, and cloud platforms has enabled an 18% reduction in energy consumption in smart manufacturing simulations. Thus, the use of IoT technologies promotes automated decision-making, which makes it possible to adjust production flows to reduce energy costs [14], And finally, literature reviews highlight that the adoption of Industry 4.0

technologies, in particular IoT coupled with cyber-physical systems, represents a fundamental lever for improving the environmental sustainability of manufacturing operations [15].

According to [18], the Internet of Things (IoT) is a key aspect of collaborative and communicative management of logistics flows, providing better visibility and synchronization of operations. Smart sensors and connected devices allow for the exchange of information in real time among stakeholders of the supply chain. Through better visibility of logistics flows, planning, and traceability, real-time information provides better responsiveness to disruptions. This collaborative approach not only helps to optimize internal logistics costs, but also plays a significant role in decreasing the energy consumption, and hence the carbon footprint of industrial processes.

2.3.2 The impact of AI integration

In Industry 4.0, the role of artificial intelligence (AI) in reducing energy consumption of industrial systems is crucial. In fact, empirical data has shown that higher levels of AI adoption are correlated to lower energy consumption with an approximate 0.48% decrease in energy consumption for every 1% increase in AI adoption in companies [16]. Also, machine learning and deep neural based plans can provide automated and predictive energy management with energy savings between 10–20% in production systems [17] and can enable predictive maintenance which can predict malfunctions and prevents unplanned shutdowns which typically contribute to thermal and energy losses [18-19].

2.4 Flow Modeling and Simulation in Smart Factory

2.4.1 Definition

The basic concept of modeling and simulation in product manufacturing is the analysis of production processes [20]. It is used to denote a material or immaterial imitation of an object, regardless of the purpose for which it is created [21]. Modeling is a theoretical and cognitive process based on abstractions. It is ideally defined as the recognition of objects through other objects, mostly artificially created. It imitates the structures and behavior of the real system [22]. The fundamental principle consists in drawing conclusions from experiments and simulations within a defined system comprising objects and their interactions.

2.4.2 Objective

The main reasons for modeling are, firstly, to support decision-making and secure investments, and secondly, to design future production units and compare solutions through complex data management. In summary, flow simulation is intrinsically part of both a strategic and operational approach, which can facilitate better management and even better adaptation of production systems [23]. Furthermore, if we consider the performance of predictive maintenance (PdM) applications, it depends on the appropriate choice of the machine learning (ML) model used to select the best machine learning model for predictive maintenance and to create a methodological framework to help companies select the machine learning model best suited to their needs and objectives [1].

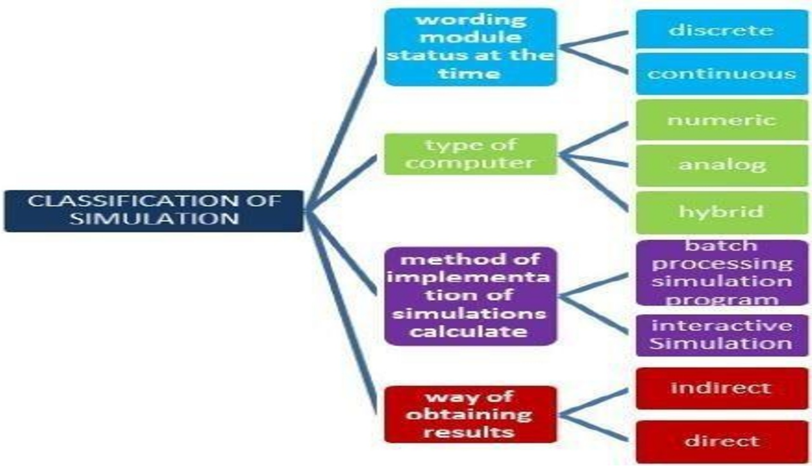

Fig. 5. Classification of simulation

2.4.3 The criteria for choosing simulation software

Choosing the right flow simulation software can be difficult because, although all of these software packages are built on similar fundamentals, each one has its own particular features, strengths, and weaknesses. The decision can also be influenced by the user's background in programming language development. Depending on the actual process being modeled, some software may be more practical or lead to improved efficiency. However, acquisition cost is a crucial factor to consider, along with additional expenses such as hardware requirements and annual maintenance fees, as is the case with Arena software, for example [24].

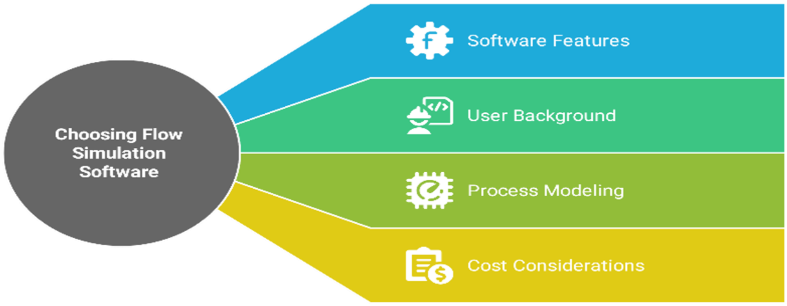

Fig. 6. The criteria for choosing simulation software

3 Related Works

The work carried out through this article is to present the methods of choosing IoT technologies and AI simulation software alternatives based on several criteria. In fact, the AHP (Analytic Hierarchy Process) method is particularly well-suited when it comes to making a structured decision involving multiple criteria, making it an excellent choice for selecting a modeling/simulation tool in a complex context such as the automotive industry.

The network selection problem uses also multi-attribute decision making (MADM) methods to improve decision making during vertical transfer.

In this work, the objective is to identify the most suitable simulation tool for modeling the effects of the Internet of Things (IoT) and Artificial Intelligence (AI) on production planning and internal logistics costs in an automotive smart factory. This choice involves taking into account several technical, functional, and industrial criteria [25].

Table 1. The objective of each method of modeling

Method	Objective
AHP (Analytic Hierarchy Process)	Decompose the problem into a hierarchy and prioritize criteria/alternatives
TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)	Rank alternatives according to closeness to the ideal solution
BWM (Best Worst Method)	Compare criteria with respect to the best and worst
VIKOR	Find a compromise solution among criteria
ELECTRE / PROMETHEE	Eliminate or outrank certain alternatives
LCA (Life Cycle Assessment)	Assess the full environmental impact of a technology
Extended Cost-Benefit Analysis	Integrate costs, benefits, and externalities
Fuzzy MCDM	Consider uncertainty and imprecision in judgments

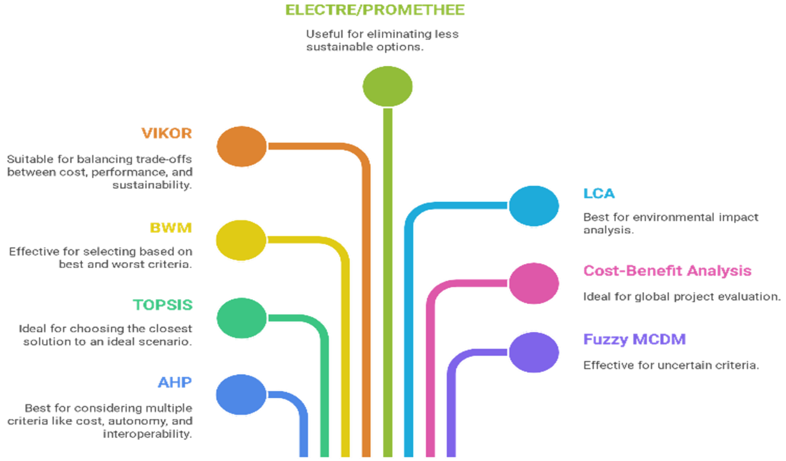

Fig. 7. The criteria's method

In our case, Industry 4.0 requires tools that must meet several simultaneous requirements: flow modeling, IoT compatibility, AI integration, 3D, ease of use, etc. In summary, AHP breaks down a complex problem into a clear hierarchy of criteria.

Other work has been carried out with the aim of providing a solution to decision-making problems encountered in information systems for supply chains in crisis situation.

4 Methodology

4.1 Choosing the optimal AI solution

The objective of the modelling is to select the most relevant AI solution to optimize production planning in an automotive smart factory. Among the existing alternatives, consider, for example, the evaluation of Heuristic AI, Machine Learning, and Hybrid AI [26].

The decision criteria are: C1 = implementation cost, C2 = forecast accuracy, C3 = compatibility with the existing system, C4 = interpretability (ability to explain results), and C5 = Energy consumption cost.

Each criterion is assigned a weight based on its strategic importance in the automotive production context. Example of weighting used:

Implementation Cost: 25%
Accuracy: 30%
Compatibility: 15%
Interpretability: 15%
Energy consumption cost: 15%

To construct the performance matrix, each alternative will be evaluated for each criterion, on a scale of 0 to 1, where:
1 represents the best performance on a given criterion,
0 represents the worst.
This results in the following performance table:

Table 2. Performance Table (IA)

Alternative	C1	C2	C3	C4	C5
Heuristic AI	0,7	0,6	0,9	0,8	0,9
Machine Learning	0,5	0,9	0,7	0,4	0,6
Hybrid AI	0,6	0,8	0,8	0,6	0,7

To calculate the weighted score for each alternative, we applied the following mathematical formula:

$$Score(Ai) = \sum j\ (Pj \times Rij) \tag{1}$$

Where:
Ai = ith alternative (e.g., Heuristic AI)
Pj = weight of criterion j (e.g., Precision = 0.30)
Rij = performance of Ai on criterion j (e.g., Heuristic AI has 0.6 in Precision)
Let's take the example calculation for Heuristic AI:
Heuristic Score = 0.25×0.7 + 0.30×0.6 + 0.15×0.9 + 0.15×0.8 + 0.15×0.9
= 0.175 + 0.18 + 0.135 + 0.12 + 0.135 = 0.745
We do the same calculation for the other AIs, which gives the following final scores:

Table 3. Score results (AI)

Alternative	Final Score
Heuristic AI	0,745
Machine Learning	0,65
Hybrid AI	0,705

The mathematical formulas used are :
Final score :

$$Score(Ai) = \sum j \ (Pj \times Rij) \tag{2}$$

Normalization (if necessary):

$$Rij\_norm = (Rij - min(Rj)) / (max(Rj) - min(Rj)) \tag{3}$$

Verification:

$$\sum j \ (Pj) = 1 \tag{4}$$

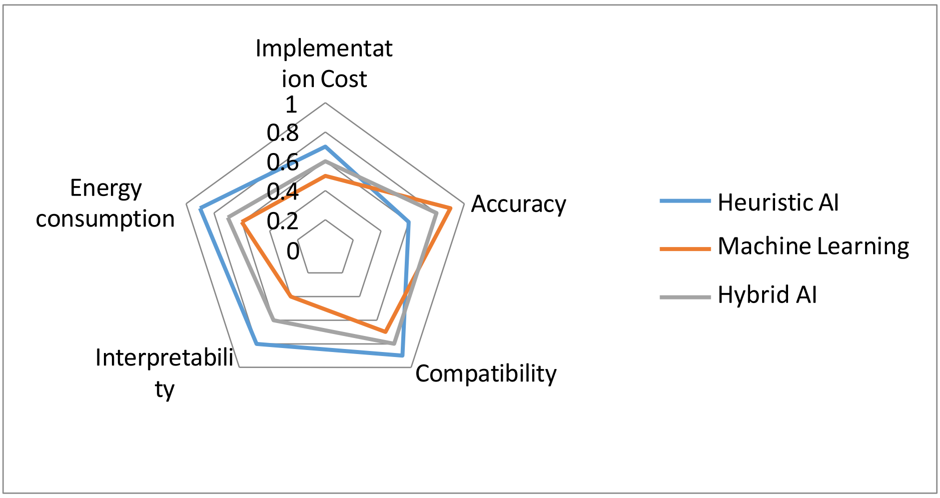

Fig. 8. Multi-criteria comparison of AI

4.2 Choosing the optimal IoT solution

To select the best IoT solution to optimize the internal production and logistics flow of an automotive smart factory, we apply the same AHP (Analytic Hierarchy Process) method with different criteria and weightings.

The alternatives studied are Passive RFID, BLE Sensor, and LoRaWAN Sensor. The criteria used are: C1 = cost, C2 = accuracy, C3 = compatibility, C4 = scalability, and C5 = energy consumption.

Each criterion is assigned a weight based on its importance. Here is the weighting used:

- Cost: 25%
- Accuracy: 25%

- Compatibility: 20%
- Scalability: 15%
- Energy Consumption: 15%

To construct the normalized performance matrix, each alternative is rated from 0 to 1 for each criterion according to its performance level:

Table 4. Performance level by criterion (IoT)

Alternative	C1	C2	C3	C4	C5
Passive RFID	0,8	0,6	0,9	0,6	0,9
BLE Sensor	0,6	0,8	0,7	0,8	0,7
LoRaWAN Sensor	0,5	0,7	0,6	0,9	0,8

Using the same formulas and steps as for AI, we obtain the following results:

Table 5. Score results (IoT)

Alternative	Final Score
Passive RFID	0,755
BLE Sensor	0,715
LoRaWAN Sensor	0,675

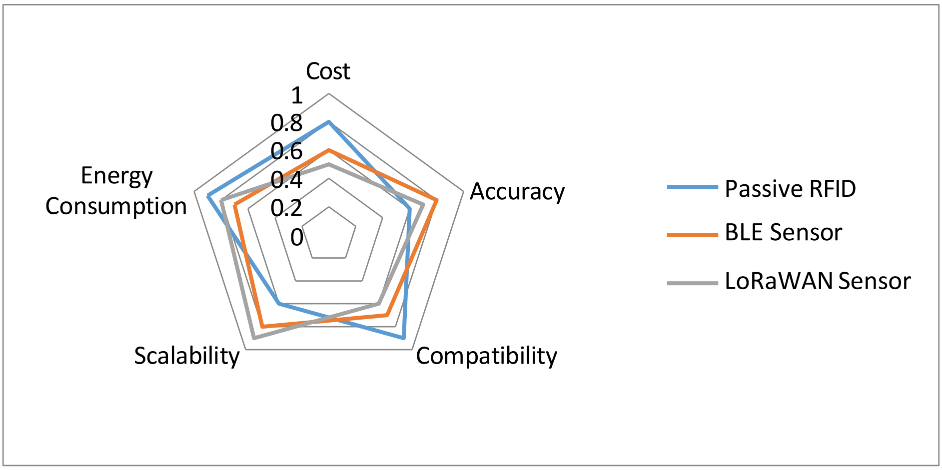

Fig. 9. Multi-criteria comparison of IoT

4.3 Choosing the production simulation tool

The objective of this section is to identify the most suitable simulation tool for an industrial digitalization project that integrates the Internet of Things (IoT) and Artificial Intelligence (AI) in a Smart Factory in the automotive sector, using the AHP (Analytic Hierarchy Process) multi-criteria method.

The criteria are C1 = Hybrid Simulation, C2 = IoT/AI Integration, C3 = 3D Visualization, C4 = Ease of Use, and C5 = Automotive Use Case. These criteria are weighted according to their strategic importance in the project:

Table 6. Criteria Weighting

Criteria	Weighting
Hybrid Simulation	30%
IoT/AI Integration	15%
3D Visualization	15%
Ease of Use	15%
Automotive Use Case	15%

The tools we will compare are AnyLogic, FlexSim, and Arena. Specifically:

- AnyLogic is a hybrid simulation (agents + discrete events), Java language, with strong integration capabilities with emerging technologies (IoT, AI, digital twins).
- FlexSim is a high-performance 3D graphics engine, strong in the simulation of physical production systems, but less scalable for digital technologies.
- Arena is the classic tool based on discrete events, widely used in academia, and poorly suited to the integration of new technologies.

Table 7. AHP Summary Table

Tool	C1	C2	C3	C4	C5	Final Score
AnyLogic	1	1	0,5	0,6	0,9	0,85
Arena	0,3	0,1	0,2	1	0,5	0,37
FlexSim	0,7	0,6	1	0,7	0,8	0,735

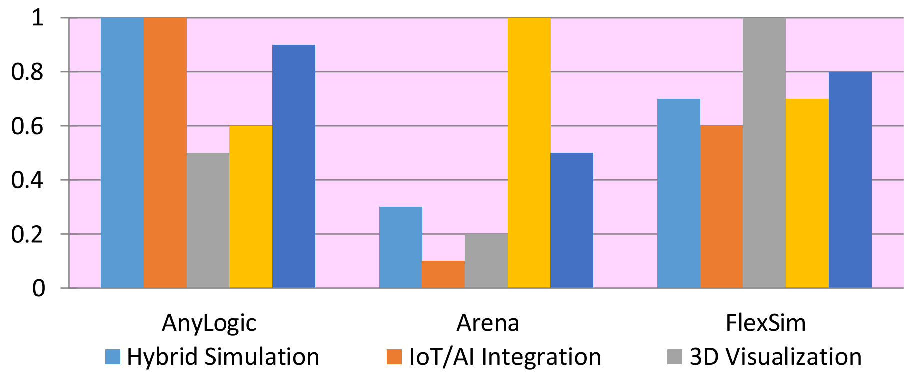

Fig. 10. Comparison of simulation tools (Bars)

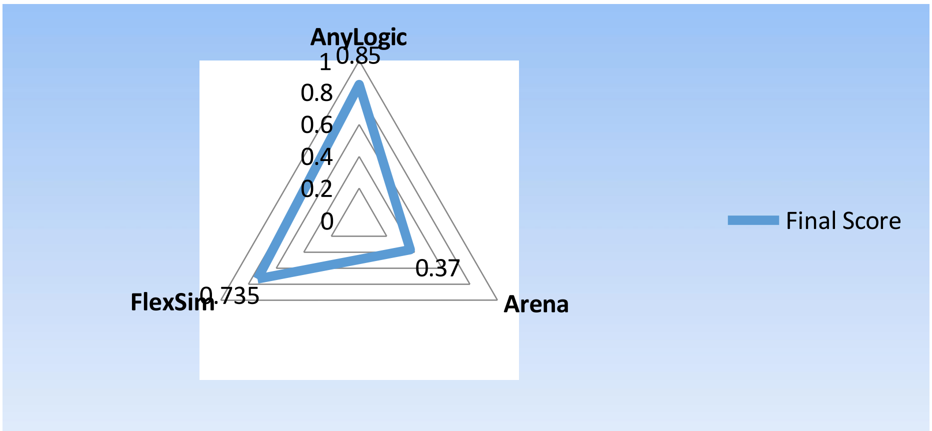

Fig. 11. Comparison of simulation tools (final score)

5 Results and discussion

Let us begin with the first analysis concerning AI. Based on the AHP analysis results, it is clear that Heuristic AI is the optimal solution in this scenario. Regarding IoT, the Passive RFID solution was the most recommended (see AHP simulation results).

Finally, as a result of this analysis, and in the context of an automotive Smart Factory aiming to streamline production and internal logistics costs through IoT and AI, AnyLogic is the most appropriate simulation tool according to the AHP method. It allows for the modeling of physical, human, and technological behaviors, with high adaptability to the requirements of Industry 4.0 and more optimized energy consumption.

6 Conclusion

The current study has demonstrated that an automotive smart factory that incorporated IoT, AI, and simulations will need to consider sustainability, in addition to technological performance. Applying the AHP-based multi-criteria approach showed that a combination of heuristic AI, passive RFID sensors, and AnyLogic simulation software provides the best balanced and, ultimately eco-efficient performance optimizing the production planning and internal logistics of smart factories, creating operational flexibility and unable to reduce internal cost, also achieving energy efficiency and reduced carbon business footprint.

The results, importantly, indicate that structured decision-making frameworks help industrial managers achieve a trade-off between competitiveness and environmental responsibility that can form the basis of a green and sustainable Industry 4.0 ecosystems. Further, these decisions are central in positioning the role of the automotive smart factory in the smart city infrastructure as it relates to interdependence between industrial performance, energy transition, and sustainability. Future research should expand the research approach to include the benchmarking of AHP with other MCDM methods (TOPSIS, BWM, VIKOR) to formulate and evaluate the decision models in actual industries to enhance the robustness of sustainable technological selection processes.

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