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Conjugation of Hypersoft Set and Triangular Neutrosophic to Evaluate Cognitive Digital Twins' Contribution to Smart Manufacturing

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Abstract: The latest innovation in digital twin technology is called Cognitive Digital Twins (CDT). The sophisticated and autonomous activities made possible by this technology have the potential to revolutionize manufacturing. An overview of CDT in manufacturing is given in this paper, along with an examination of their main features, components, and possible uses. CDT can learn from data, reason about difficult circumstances, and make well-informed judgments by combining artificial intelligence, machine learning, and knowledge representation approaches. The advantages of CDT in smart manufacturing are covered in the paper. Hence, the objective of this paper is evaluating the smart manufacturing that adopts CDT in its operations and practices to be smart. Multi-Criteria Decision Making (MCDM) as CRiteria Importance Through Intercriteria Correlation and multi-objective optimization based on simple ratio analysis (MOOSRA) are leveraged to construct soft decision models. This model can trat with vague and incomplete information through harnessing uncertainty theory especially Triangular Neurosophic Number (TriNN). Also, Hypersoft set is utilized with MOOSRA to rank alternatives of smart manufacturing

Keywords: smart manufacturing; cognitive digital twin; CRITIC technique; MOOSRA technique; Hpersoft set;Triangular Neurosophic Number.

1. Introduction

Manufacturing is one of the foremost sectors that has an immense influence on a nation's economy and development [1] . As well as [2] making products that meet consumer demand, is one of the sustainable manufacturing objectives. The notion of sustainable manufacturing (SusM) [3]has gained widespread support in business, particularly in industry, and is receiving more attention in the research community within the broader topic of sustainability.

From the perspective[4] adopting sustainability ideas and technologies that impact manufacturing's performance is crucial for practitioners, policymakers, and manufacturers.

Researchers, governments, society, and the manufacturing industrial sector have all shown a great deal of interest in sustainability according to [5]. This heightened emphasis on sustainability is motivated by the need to remain competitive in a globalized economy and adjust to quick changes in consumer needs. Whereby [6] linked the concept of sustainability with influential aspects such as environmentally: diminishing the influence on the environment by cutting back on pollution, waste production, and resource consumption [7]; Economically: Putting into practice economical,

sustainable methods that don't substantially raise manufacturing costs [8]; Ingenuity :Putting expenditures on research and development to develop new environmentally friendly technology and procedures[9]. Socially: emphasizes the welfare of employees, local communities, and society [10].
Surveying prior scholars' perspectives as[11],[12], [13] demonstrated that deploying the notion of sustainability in manufacturing has a favorable impact. In this context, Figure 1 compiled these perspectives on bolstering aspects of sustainability in manufacturing.

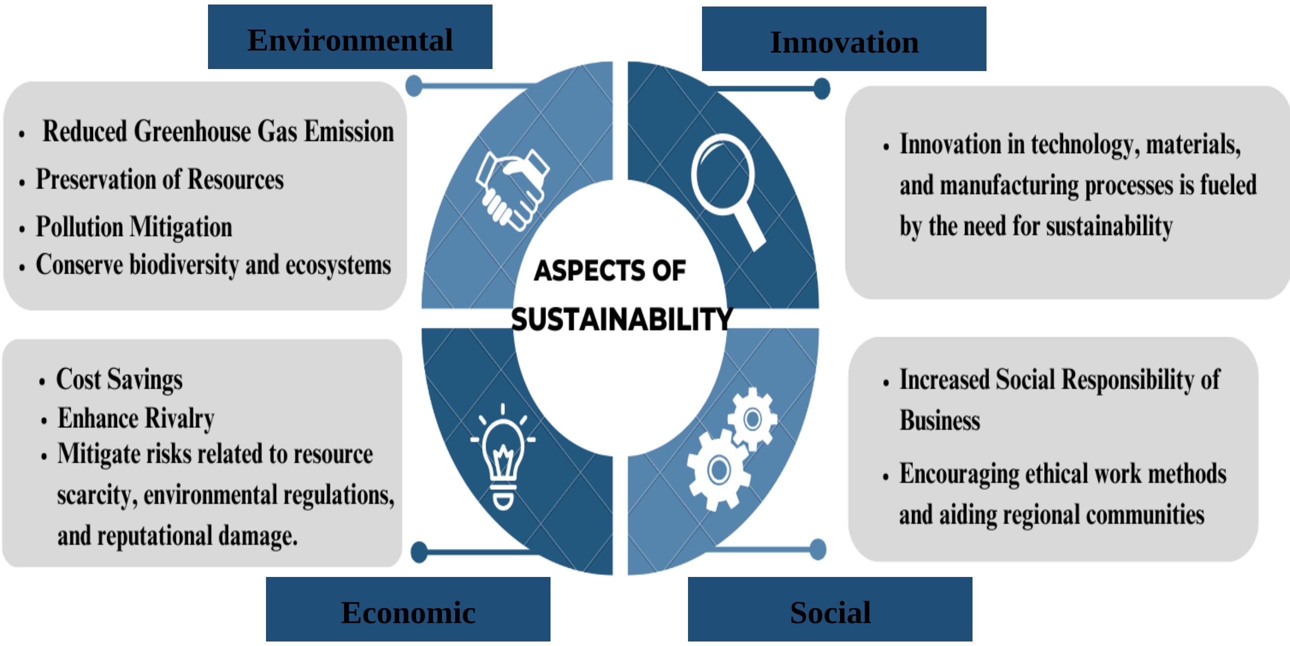

Figure 1. Sustainability in Manufacturing

On other side, [14] stated that a significant contributor to climate change and one of the biggest worldwide sources of carbon emissions is the manufacturing sector. Accordingly manufacturers are coming under more pressure to lower their carbon impact and actively promote environmental goals[15]. Hence, many stakeholders have started to put pressure on firms to implement sustainable practices after realizing the impact on the environment.
The sustainability of manufacturing is hampered by several obstacles, despite its significance. These obstacles discussed in [16] that entailed in domestic disturbances to worldwide calamities as diseases (Covid 19), floods that threaten the sustainability of manufacturing.
Scholars in [17] assumed another obstacles as accurate decision making based on predicting equipment failures through analyzing real-time data to avoid malfunctions that can cause interruptions in production and problems with quality [18].
To fix this obstacle, scholars in [19] utilized digital technologies as artificial intelligence (AI) and its subset machine learning(ML) and deep learning(DL) to enhance demand forecasts after that, allowing producers to maximize inventory control and production scheduling.
Generally, deploying digital technologies, industry 4.0, and industry 5.0 enable manufacturing to be automated, digital and smart. These technologies [20] reduce manual labor, increasing production speed, and minimizing errors.

Smart manufacturing is a contemporary strategy that integrates cutting-edge technology like cloud computing, artificial intelligence, and the Internet of Things (IoT) into manufacturing processes in tandem with sustainable production[21] .Manufacturing systems can now independently sense their surroundings, make the best judgments, and carry out jobs with accuracy thanks to this connection. Thus, smart manufacturing minimizes errors and waste while increasing production precision and efficiency[22]

By enabling production that is more flexible, adaptive, and customized to meet the demands of individual customers, this transition toward smart manufacturing opens new prospects for industries worldwide [23]. Whereas creates a digital replica of a physical object or process by digital twins (DTs) enabling better understanding, optimization, and improved lifecycle management. Falekas et al.[24] described DTs as virtual mirrors of physical systems that allow for real-time monitoring, analysis, and optimization, have been developed to improve smart manufacturing. DTs can increase the efficiency and quality of item production, forecast equipment breakdowns, and simulate production processes in smart manufacturing

Digital twins give businesses comprehensive insights into the performance and behavior of physical assets using data analytics and machine learning, enabling them to foresee problems and make data-driven modifications [25].The paper emphasizes that digital twins are vital to future technology advancements across industries, offering potential cost savings, improved decision-making, and enhanced operational efficiency. Scholas [26] showcases an advanced form of a digital twin that integrates cognitive computing capabilities, this form entailed in cognitive digital twin (CDT). In the same vein [27] CDT defined as an expansion of pre-existing digital twins, cognitive digital twins include three levels access, analytics, and cognition. These layers include extra communication, analytics, and intelligence capabilities. In light of CDT and cognitive computing, ML , DL are utilized to analyze data from the physical twin and other sources to identify patterns, trends. Based on knowledge gained from analyzing data, it can forecast outcomes, offer suggestions, and even manage some physical system components on its own. Accordingly, various studies employed CDT in various purposes as [28] that leveraged CDT in smart manufacturing to Identify inefficiencies and bottlenecks in production data analysis, then suggest adjustments to improve the process.

In this context, this paper involves CDT producing accurate results as it acts as human being, by incorporating human cognition through AI and Semantic Web technologies into the design of autonomous manufacturing. wherein CDT [29] aims to improve autonomous manufacturing by enabling manufacturing resources to think, learn, and comprehend the dynamics of industrial environments.

The importance of CDT in manufacturing to be smart and sustainable is the objective of our study. Hence, we evaluate the role of CDT in manufacturing to be sustainable through constructing a robust soft decision model. The evaluation is conducted based on a set of criteria.

To objectively evaluate and assign priority levels, the CRITIC technique is leveraged in our soft decision model to offer a quantitative approach by examining the correlations and differences between criteria. This guarantees that the criteria's weighting is objective and data-driven, reflecting actual significance rather than personal opinion[30] .One major advantage of this technique, particularly the suggested methodology based on CRITIC principles, lies in its objectivity and structured computation process. This method uses a systematic, straightforward calculation process to generate criteria weights, ensuring clarity and reducing complexity. Consequently, CRITIC method enables decision-makers to effectively prioritize criteria, which can be especially useful in fields where decision accuracy and consistency are crucial. This objective framework allows for repeatable, reliable results that are essential for robust decision-making and analysis in complex scenarios.

MOOSRA technique is a powerful multi-criteria decision-making tool that ranks alternatives based on performance across multiple criteria [31]. It accounts for both maximizing and minimizing attributes and is particularly effective in handling significant variations in criteria values.

These MCDM techniques are combined with TriNN and Hypersoft sets to bolster decisions of decision makers in vague situations and incomplete information.

2. Literature review

Decision-making in smart manufacturing has advanced significantly because of automation and data integration technology. The ability of manufacturing systems to make decisions is being shaped by linked devices, data analytics, and artificial intelligence (AI), according to recent research. The move to data-centric, AI-driven frameworks is a significant trend that enables manufacturers to use real-time data to make better education, predictive decisions to reduce downtime and improve operational efficiency,this strategy aids in the identification of bottlenecks, production optimization, and proactive equipment maintenance management.

Here is a related work which focuses on smart manufacturing and decision-making. These papers cover topics like the use of AI, IoT, big data analytics, and decision support systems in enhancing decision-making capabilities within smart manufacturing:

Implementing the Internet of Things (IoT) in smart manufacturing within sustainable supply chain management (SSCM) offers several issues, especially regarding scalability, energy consumption, security, and privacy. Although these obstacles have been highlighted in earlier research, a methodical strategy to overcome them in smart manufacturing settings is still developing. To evaluate and prioritize various IoT issues, this research presents a decision-making framework that integrates q-Rung Orthopair Fuzzy sets, CRITIC, and VIKOR methodologies. This paradigm improves resource allocation and decision-making precision in smart manufacturing by enabling accurate prioritizing. The model can be used to solve IoT complications in SSCM for smart manufacturing environments because of its reliability, which has been validated by sensitivity analysis and comparisons with alternative approaches [32].

Since they enable more customization, efficiency, and productivity, Industry 4.0 technologies like IoT, big data, and CPS are crucial to the growth of smart manufacturing. However, utilizing these technologies requires both technological innovation and a trained workforce. They go over important Industry 4.0 subjects and worker competencies needed for future smart factories to aid with the transition to intelligent production [33].

Sanusi et al. [34]looked at the adoption of smart manufacturing in Indonesian SMEs and identified several obstacles, including a lack of funding, poor infrastructure, and a lack of skilled workers. They show how even little investments in automation may significantly increase productivity and cut costs in their case studies of South Sulawesi SMEs.The report emphasizes the importance of business and governmental cooperation in removing adoption hurdles, highlighting Indonesia's "Making Indonesia 4.0" effort. According to Sanusi et al., stakeholders should work together to encourage SME digital transformation in developing nations by offering financial and policy assistance.

A digital twin-assisted model was created to maximize collaborative production in smart systems. Effective resource allocation and proactive equipment management are made possible by the model's combination of digital twin technology and predictive diagnostics using Elman neural networks and IVIF-TOPSIS. To improve supply chain KPIs like efficiency and adaptability and enables businesses to respond quickly to market demands, it also integrates a value co-creation framework [35].

A key component of smart manufacturing, digital twins improve output through data-driven optimization, simulation, and real-time monitoring. By building virtual versions of actual processes, digital twins facilitate flexible and responsive decision-making in the context of smart manufacturing. Their effects on lowering downtime, enhancing quality, and anticipating maintenance requirements—all crucial components of a smart manufacturing system—have been shown in earlier research. Digital twins support smart manufacturing's emphasis on flexibility and efficiency by helping producers find inefficiencies and make changes without interfering with real operations by mimicking production settings.

The application of CDT in manufacturing is examined with a focus on how they can convert conventional digital twins into sentient, intelligent beings. Access, analytics, and cognition are the three levels that make up CDTs. providing a path for completely autonomous, cross-domain manufacturing systems that make use of knowledge graphs, semantic reasoning, and artificial intelligence (AI) technologies, as well as a prototype that has been evaluated using production line performance statistics [36].

3. Methodology

3.1 preliminaries and definitions

In this subsection, a set of definitions and preliminaries related to HyperSoft and utilized techniques that contributed to constructing soft decision model.

The HyperSoft defined and proposed by Smarandache [37]:

- Let μ be a universe of discourse, (μ) the power set of μ, and A a set of attributes. Then, the pair (F, μ), F: $A \rightarrow (\mu)$ is called a Soft Set over
- $Let\ a1,\ a1\ ,\ \ldots\ an\ for\ n \geq 9$, be n distinct attributes,

Whose corresponding attributes are respectively the set $A1\ ,\ A1\ ,\ \ldots\ An\ with\ Ai \cap Aj = \emptyset,\ for\ i \neq j,\ and$ $i,j \in \{9,1,\ \ldots\ n\}$.

- Then the pair (F: $A1 \times A1 \times \ldots\ An \rightarrow (\mu)$) is called a HyperSoft over μ.

3.2 Soft Decision Model: Procedures of Proposed Model

This subsection provides the techniques we use to find the weights for each criterion the techniques for ranking the alternatives of smart manufacturing that adopt CDT in its operations and manufacturing to choose the suitable alternative with the best results.

3.2.1 Create the decision matrix

1. Determining the alternatives and criteria for the problem
2. Evaluating the alternatives based on the criteria by formed expert panel
3. Create the decision matrix according to the scales mentioned in Table 1.
4. use Eq.1 to convert the triangular neutrosophic scale into deneutrosophic value.

$$\text{Score}(Qij) = \frac{\text{lij+mij+uij}}{9} * (2 + T - I - F) \tag{1}$$

Where: i=1,2,3,…m; n=1,2,3,….. j; l, m, u refer to the lover, middle, and upper values and T,I, F refer to truth, indeterminacy and false respectively.

5. Combine the decision matrices of each decision maker into a single decision matrix by using Eq. 2.

$$xi = \frac{\sum_{j=1}^{N}(\text{Qij})}{\text{N}} \tag{2}$$

Where Qij is the value of each criterion and N is number of decision makers.

Table 1.Linguistic triangular neutrosophic scale

Crisp Scale	Explanation	TriNN Scale
1	Equally Essential	<<1,1,1>;0.5,0.5,0.5>>
2	Slightly Moderately	<<1,2,3>;0.4,0.6,0.65>>
3	slightly Essential	<<2,3,4>;0.3,0.75,0.7>>
4	Minor To Strong	<<3,4,5>;0.35,0.6,0.4>>
5	Mighty Essential	<<4,5,6>;0.8,0.15,0.2>>
6	Slightly Strong Essential	<<5,6,7>;0.7,0.25,0.3>>
7	High Strong Essential	<<6,7,8>;0.9,0.1,0.1>>
8	Very High Strong Essential	<<7,8,9>;0.85,0.1,0.15>>
9	Absolutely High Essential	<<9,9,9>;0.1,0.0,0.0>>

3.2.2 CRITIC Method

6. Normalize the aggragated matrix using Eq.3, Eq.4

$$\text{Rij} = \frac{xij - \min(xij)}{\max(xij) - \min(xij)} \text{ for benefit criteria} \tag{3}$$

$$\text{Rij} = \frac{\max(xij) - xij}{\max(xij) - \min(xij)} \text{ for non benefit criteria} \tag{4}$$

7. Calculate the standard deviation (sd) of the matrix with Eq. 5

$$sd=\sqrt{\frac{\sum_{i=1}^{m}(Rij-\bar{R}j)}{m}}\ ,\ \bar{R}=\frac{1}{m}\sum_{i=0}^{m}(Rij) \tag{5}$$

8. Calculate correlation between each criteria using Eq. 6

$$cjk=\frac{\sum_{j=1}^{m}(Rij-\bar{R}j)(Rik-\bar{R}k)}{=\sqrt{\sum_{j=1}^{m}(Rij-\bar{R}j)^2\sum_{j=1}^{m}(Rik-\bar{R}k)^2}} \tag{6}$$

9. Calculate the convert degree rij using Eq.7

$$rj=\sum_{i=1}^{m}(1-cjk) \tag{7}$$

10. calculate the weight using Eq.8

$$wj=sd^*\left(\frac{ri}{\sum_{j=1}^{n}ri}\right) \tag{8}$$

3.2.3 MOOSRA Method

1. Normalize the aggregated decision matrix by Eq. 9

$$Xij^*=\frac{\sum_{j=1}^{m}Xij}{=\sqrt{\sum_{i=1}^{n}(Xij)^2}} \tag{9}$$

2. Create weighted normalize decision matrix by Eq 10

$$z=Xij^*wj \tag{10}$$

3. Rank the alternatives by Eq. 11

$$si=\frac{\sum benefit\ value}{\sum non\ benefit\ value} \tag{11}$$

4 Real case study

To validate the accuracy of constructed soft decision model, we communicate with manufacturing that adopting CDT in its operations and manufacturing. Hence, in our study four smart manufacturing contributed to our evaluation process to be alternatives. The evaluation is conducted based on five criteria and five attributes.

4.1 identify attributes, set of criteria and alternatives.

Herein five criteria, four alternatives and the attributes related to the criteria ae determined.
We have 5 criteria and 4 alternatives (SM) in this study depending on decision makers' opinions we use 4 attribute values (with 14 sub-attributes) for all criteria
The criteria we identified:
C1= production (benefit)
C2= efficiency (benefit)
C3= Flexibility (benefit)
C4= complexity (non- benefit)
C5= costs (non- benefit)
The attributes values are:
A1={{A1-1=high}, {A1-2=moderate}, ({A1-3=low}}

A2={{A2-1=>55%},{A2-2=25-55%},{A2-3= <30%}}

A3={{A3-1=>Acceptable},{A3-2=<Non-acceptable}}

A4={{A4-1=high}, {A4-2=moderate}, {A4-3=low}}

A5={{5-1=<2 million $},{5-2=2-5 million $},{A5-3=>5 million $}}

4.2 valuating criteria and attribute values

- Valuating Criteria Weight: CRITIC-TriNN

We applied critic method with TriNN to obtain weight

Table 2. Normalize aggregated matrix

	C1	**C2**	**C3**	**C4**	**C5**
SM1	0.376984	0.061047	1	0	0.222656
SM2	1.178571	1	0.588235	0.612774	1
SM3	0	0.22093	0.066176	1	0.841797
SM4	1	0	0	0.0499	0

Table 3. Finding correlation between each criterion

	C1	**C2**	**C3**	**C4**	**C5**
C1	1	0.503829	0.017161	-0.36938	-0.07155
C2	0.503829	1	0.20446	0.453134	0.806848
C3	0.017161	0.20446	1	-0.38594	0.018747
C4	-0.36938	0.453134	-0.38594	1	0.864689
C5	-0.07155	0.806848	0.018747	0.864689	1

Table 4. Convert the degree (rij)

	C1	**C2**	**C3**	**C4**	**C5**
C1	0	0.496171	0.982839	1.369376	1.071552
C2	0.496171	0	0.79554	0.546866	0.193152
C3	0.982839	0.79554	0	1.385939	0.981253
C4	1.369376	0.546866	1.385939	0	0.135311
C5	1.071552	0.193152	0.981253	0.135311	0

Table 5. Final Criteria Weights

	sd	rij	Cj	wj	wj%
C1	0.547245	3.919938	2.145167	0.274061	27%
C2	0.462483	2.03173	0.93964	0.120046	12%
C3	0.471215	4.14557	1.953455	0.249569	25%
C4	0.478491	3.437492	1.644809	0.210137	21%

C5	0.480523	2.381268	1.144253	0.146187	15%
Sum			7.827324	1	100%

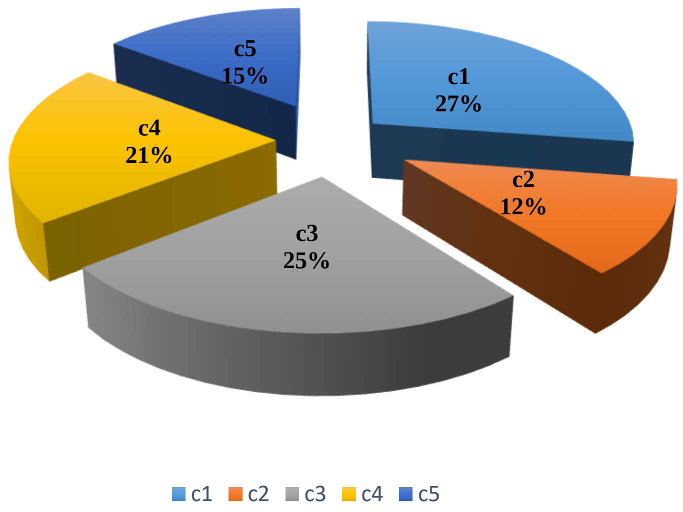

Figure 2. Weights of the criteria using CRITIC

4.3 Ranking alternatives using (MOOSRA-Hypersoft Set) and TirNN

Since C=C1,C2,C3,C4,C5 are contributed to ranking process for four alternatives. We deploy hypersoft set methodology with TriNN in MOOSRA to rank four alternatives. Hence, we are leveraging attributes (A1-1:A5-3), then we choose A1-1,A2-1,A3-1,A4-3,A5-1.

Table 6. square the decision matrix

	A1-1	**A2-1**	**A3-1**	**A4-3**	**A5-1**
SM1	5.867160494	2.46025034	5.653827	21.10892	4.85631
SM2	21.77777778	4.69444444	3.853224	8.345679	2.151111
SM3	1.867777778	2.79013717	2.065075	3.280123	2.613611
SM4	17.36111111	2.3397668	1.877915	19.85198	5.831331
sum	46.87382716	12.2845988	13.45004	52.5867	15.45236
root	6.846446316	3.5049392	3.66743	7.251669	3.930949

Table 7. Normalize decision matrix.

	A1-1	**A2-1**	**A3-1**	**A4-3**	**A5-1**
SM1	0.856964361	0.7019381	1.541632	2.910905	1.235404
SM2	3.180887832	1.33937971	1.05066	1.150863	0.547224
SM3	0.272809819	0.79605865	0.563085	0.452327	0.66488
SM4	2.535784305	0.66756274	0.512052	2.737573	1.483441
Wj	0.274061343	0.12004614	0.249569	0.210137	0.146187

Table 8. Weighted normalized decision matrix

	A1-1	A2-1	A3-1	A4-3	A5-1
SM1	0.234860804	0.08426496	0.384743	0.611688	0.1806
SM2	0.871758392	0.16078736	0.262212	0.241839	0.079997
SM3	0.074766625	0.09556377	0.140528	0.09505	0.097197
SM4	0.694960453	0.08013833	0.127792	0.575265	0.21686

Table 9. ranking the alternatives.

	sum of benefits	sum of non-benefits	Si	Ranking
SM1	0.703868797	0.79228838	0.8884	4
SM2	1.294757686	0.32183585	4.023038	1
SM3	0.310858812	0.19224739	1.616973	2
SM4	0.902890927	0.79212478	1.139834	3

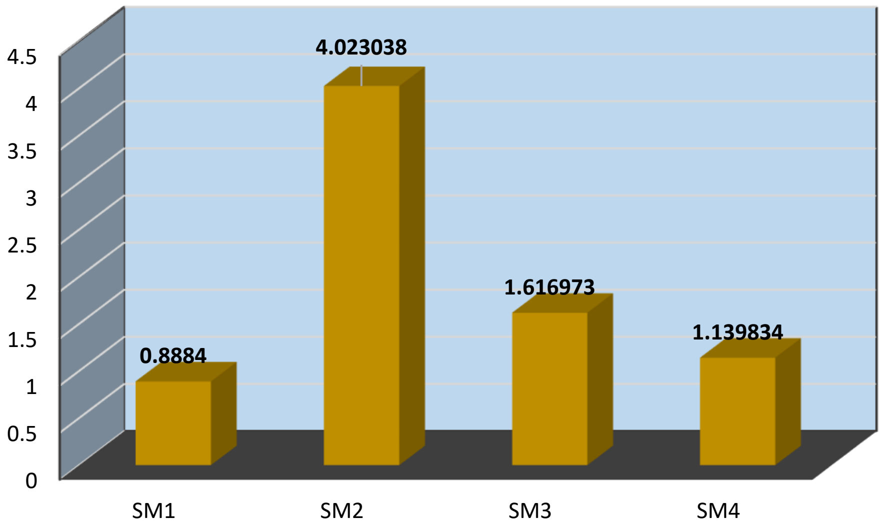

Figure 3. Ranking of Alternatives

5 Conclusion

This paper has investigated the optimization of multi-robot collaborative systems within smart manufacturing through the integration of cognitive digital twins and advanced decision-making methodologies. We present a framework for selecting the most suitable machine for smart manufacturing based on several factors and criteria. The main criteria considered include Production (C1), Efficiency (C2), Survivability (C3), Complexity (C4), and Costs (C5). Four different machine alternatives were evaluated in this paper.

The proposed MCDM techniques are working under authority of Hypersoft set and TriNN for selecting the most suitable alternative of smart manufacturing. By leveraging the CRITIC method to determine the weights of criteria and the MOOSRA technique to rank the alternatives, this study ensures an objective and data-driven evaluation process. The results demonstrate that the proposed approach provides more reliable and actionable insights compared to traditional methods, offering a practical guide for managers to prioritize strategies effectively. This research reinforces the importance of integrating Industry 4.0 technologies to enhance efficiency, sustainability, and decision-making in manufacturing to be smart. The findings of the constructed soft decision model indicated that SM2 ia the optimal alternative otherwise SM1 is the worst alternative.

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