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Clarivate Optimal Livestock via Enigmatic Nature of Blended Decision-Making Paradigm: Practicing Comparative Methodologies

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Abstract

Deployment of the intelligent technologies of information and communication technologies (ICTs) in livestock farming has positive impact and transforms it into precision livestock farm (PrLF). As well the concept of smart livestock farming is paired with technologies of Internet of Things (IoTs), virtual reality (VR), artificial intelligence (AI)…etc. The objectives of smart livestock are enriching the livestock industry's operational efficiency, ecological sustainability, and economic viability. Thus, a variety of aspects, such as human resources, product prices (both agricultural and livestock), animal welfare, and environmental sustainability, will benefit from real livestock farming using technologies of blockchain (BC), digital twin (DT) and management. Accordingly, determining the best livestock that embracing the technologies of ICTs to be precision and smart is inevitable. Therefore, this study constructed a robust paradigm to take responsibility of selecting the smartest livestock farming. Criteria Importance Through Intercriteria Correlation (CRITIC) and Multi-Attribute Rating Comparison and Improvement Analysis (MARCIA) of multi-criteria decision making (MCDM) methods are integrated to analyze the alternatives of livestock framings based on set of criteria and obtaining weights for the determined criteria through CRITIC. These weights of criteria are leveraging into MAIRCA to rank the alternatives of livestock farming. The primary characteristic of this paradigm is its ability to treat incomplete and uncertain information due to collaborating uncertainty theory as single valued neutrosophic (SVN). For validating the robustness of constructed paradigm, we applied it into real case study and comparing it with other methods. The findings of the applied methods agree with constructed paradigm's findings.

Keywords: Precision Livestock Farm, Smart Livestock, Information and Communication Technologies, Multi-Criteria Decision Making, Single Valued Neutrosophic.

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1 | Introduction

Livestock farming plays a crucial role in our lives as it is one of the most important and effective sources of food products for the world's population. livestock farming is considered the main source of protein food products such: as meat, eggs, and milk[1]. In developed countries, the increasing populations have led to increased demand for livestock products, which puts pressure on farmers to increase the productivity and efficiency of livestock products[2].To solve these challenges, the Use of modern information technology is employed to convert traditional livestock to smart [3].

Smart livestock farming involves the use of new technologies such as IoT, blockchain, digital twins, smart sensors, detectors, real-time monitoring and control of production, animal welfare, and health, as well as environmental conditions to improve production as well as maximize efficiency[4]. In traditional livestock farming, the experience of the producer is base for decisions but in smart livestock farming, the decision is based on analysis of data obtained using new technologies[5]. Also, the selection process of the best smart livestock farming is hard as it includes a variety of criteria and multiple options to be considered which require a robust technique to handle all of this. Multi-Criteria Decision Making (MCDM) includes a variety of methods to determine the best option while considering multiple criteria in the selection process. moreover, it can deal with both quantitative and qualitative data [6, 7].

In recent years, the valued Neutrosophic (SVN) set theory has gained attention as a powerful tool for handling uncertainty and vagueness in decision-making processes. By incorporating SVN theory into MCDM models, researchers have been able to effectively deal with imprecise and incomplete information when selecting smart livestock farming [8, 9].

The objective of this paper is to illustrate the impact of new technology in traditional livestock farming to be smart and propose a novel model for the selection of the best smart livestock farming considering incomplete and imprecise information.

The paper sequence is as follows: Section 2 provides an overview of the impact of technology on traditional livestock farming; Section 3 introduces the concepts, and operation formulas of SVNs. Section 4 the proposed model is presented. Section 5 provides a description of the application and results of the proposed framework. Section 6 provides sensitivity and Comparative analysis. Section 7 summarizes our conclusions.

2 | Contributions of Advanced Technologies in Livestock: Toward Smart Livestock

In this section, we will discuss the different technologies and their impact on traditional livestock farming to be smart. The contributions of ICTs to livestock to be precision and smart are exhibited in the form of a group of hypotheses.

2.1 | H1: The Capacity of Farmers to Keep an Eye on the Health of Their Animals and Take Preventative Measures

IoT technology allows farmers to remotely monitor the health and behavior of animals using sensor technologies. Also, IoT sensors enable farmers to track vital signs such as heart rate, respiratory rate, rumination, blood pressure, temperature, and activity levels of animals. With the help of this data, farmers can easily detect early signs of illness in their animals, allowing early treatment. Moreover, IoT can provide information about patterns of animal behavior, helping farmers to enhance schedules of feeding and entire animal welfare [10-12].

Furthermore, IoT enables data collecting on environmental conditions such as temperature, humidity, and air quality, so farmers can make informed decisions about housing conditions and ventilation systems. This can lead to improved animal comfort and reduced stress levels, ultimately enhancing productivity and growth rates [13, 14].

As IoT allows machines to be connected across the internet this converts traditional tasks which require many workers, time, and a lot of costs to be done automatically. This task includes feeding, watering, and monitoring. In automated feeding systems, animals will get the required number of feeds at optimal times, minimizing waste and guaranteeing that animals receive the nutrients they need for development and growth. Similarly, Automated irrigation systems can ensure a constant supply of clean water for livestock while minimizing labor costs for farmers [15, 16].

In addition to improving efficiency, and productivity and reducing costs[12], by analyzing data collected by IoT technologies including sensors and devices, farmers can identify trends and patterns that can inform strategic planning and management practices. For example, predictive analytics can help farmers anticipate disease outbreaks or optimize breeding programs based on genetic traits[10, 11, 16].

Generally, the impact of IoT on traditional livestock farming is great. By using technology to monitor animals' health and behavior, automate tasks, and optimize environmental conditions farmers can improve efficiency, productivity, and profitability in their operations.

2.2 | H2: Guaranteeing the Integrity of Data and the Accessibility of Information and Transactions to Trustworthy Partners

BCT allows for the secure and immutable recording of transactions, making it an ideal tool for tracking the movement of livestock from farm to fork. Blockchain technology has an impact on traditional livestock farming by providing consumers with greater transparency and trust in the food they purchase. Consumers can easily access information about where their food comes from, how it was produced, and any certifications or quality standards it meets because every step of the supply chain is recorded on a blockchain. This level of transparency can help to increase consumer trust in the safety and sustainability of traditional livestock farming practices[17-19].

In addition to providing transparency, blockchain technology can also improve traceability in traditional livestock farming. By recording each transaction on a blockchain, farmers and producers can easily track the movement of their livestock throughout the supply chain. This can help identify any potential problems or contamination events more quickly, allowing for faster response times and lowering the risk of widespread outbreaks[20, 21].

Furthermore, blockchain technology can improve efficiency in traditional livestock farming by streamlining processes like record-keeping, inventory management, and payment. Farmers and producers can save time and resources by automating these tasks using blockchain smart contracts, while also ensuring accuracy and regulatory compliance[21, 22].

In general, blockchain technology's impact on traditional livestock farming looks vital. Blockchain technology, by providing transparency, traceability, and efficiency in the supply chain, has the potential to enhance consumer trust, food safety, and operational effectiveness in traditional livestock farming.

2.3 | H3: Emulating Various Situations using Digital Replicas of Actual Things or Systems for Tracking, Evaluating, and Improving Their Physical Equivalent in the Real World

DT refers to virtual replicas of physical objects or systems that can be used for monitoring, analyzing, and optimizing their real-world counterparts[23]. In the context of traditional livestock farming, DT has the potential to revolutionize the way farmers manage their animals and operations[24].

DT has an impact on traditional livestock farming by improving animal health and welfare, by using IoT technologies to collect data on individual animals, farmers can create digital twins that provide real-time insights into the well-being of each animal. This allows farmers to quickly identify any issues or abnormalities and take proactive measures to handle them, ultimately leading to healthier and happier animals [25, 26].

DT can enhance farm operations and increase productivity in addition to enhancing animal health. By simulating different scenarios and analyzing data from various sources, farmers can make more informed decisions about feeding schedules, breeding programs, and resource allocation. This can lead to reduced costs, increased productivity, and overall better management of the farm [26, 27].

Moreover, DT allows farmers to monitor environmental conditions in real-time and make adjustments as needed. Farmers, for example, can ensure that their animals are in the best possible conditions for growth and development by monitoring temperature levels in barns and water quality in drinking troughs[28, 29].

Overall, the impact of digital twins on traditional livestock farming is significant. By leveraging technology to create virtual replicas of their operations, farmers can improve animal health and welfare, optimize farm operations, and increase efficiency. As technology continues to advance, the potential for digital twins to transform the way livestock farming is conducted will only continue to grow.

3 | Basics of Neutrosophic Sets

In this section, important definitions of neutrosophic sets, single-valued neutrosophic sets, single-valued neutrosophic numbers, and operations on single-valued neutrosophic numbers are illustrated clearly [30, 31].

3.1 | Neutrosophic Sets

Suppose P to be a space of points and p ∈ P. A neutrosophic set H in P is characterized by a truth-membership function TH(p), indeterminacy-membership function IH(p), and a falsity membership function FH(p), where TH(p), IH(p), and FH(p) are real standards or a non-standard subset of]-0,1+[.also TH(p);P →]-0,1+[, IH(p) ;P →]-0,1+[and FH(p);P →]-0,1+[. The sum of the three membership TH(p), IH(p), and FH(p) have no restrictions, so 0− ≤sup TH(p)+ sup IH(p) + sup FH(p) ≤3+.

3.2 | Data Preprocessing

An SVNS H across P taking the form H= {⟨p, TH(p), IH(p) ,FH(p) ⟩; p ∈ P} TH(p) , IH(p) ,FH(p); P→ [0, 1] with 0≤ TH(p)+IH(p)+FH(p)≤3 ∀ p ∈ P. The single-valued neutrosophic (SVN) number is shown by = (w, x, y) where w, x, y ∈[0,1] and w+x+y≤3.

3.2.1 | Some Operations of SVNNs

Let H= {⟨p, TH(p), IH(p) ,FH(p) ⟩ ; p ∈ P}, I= {⟨p, TI(p), II(p) ,FI(p) ⟩ ; p ∈ P} be any two SVNNs with TH(p), IH(p) ,FH(p), TI(p), II(p) ,FI(p)∈[0,1] , 0≤ TH(p), IH(p) ,FH(p) ≤ 3 and 0≤ TI(p), II(p) ,FI(p) ≤3

- Complement: H^{c}= {⟨p, FH (p), 1- IH(p), TH(p) ⟩; p ∈ P}.
- Inclusion: H ⊆ I if and only if TH(p) ≤ TI(p), IH(p) ≥ II(p), FH(p) ≥FI(p) for p ∈P.
- Equality: H=I if and only if H ⊆ I and I ⊆ H.
- Union: H∪I = {⟨p, TH(p)∨TI(p), IH(p)∧II(p), FH(p)∧FI(p) ⟩; p ∈ P}.
- Intersection: H∩I = {⟨p, TH(p) ∧TI(p), IH(p) ∨II(p), FH(p) ∨ FI(p) ⟩; p ∈ P}.
- Subtraction: H-I=$\left\{\left\langle x,\frac{T_H(p)-T_I(p)}{1-T_I(p)},\frac{I_H(p)}{I_I(p)},\frac{F_H(p)}{F_I(p)}\right| |p\in P\right\}$, valid if and only if $H\geq I, T_I(p)\neq 1$, $I_I(p)\neq 0, F_I(p)\neq 0$.
- Division: H/I = $\left\{\left\langle p,\frac{T_H(p)}{T_I(p)},\frac{I_H(p)-I_I(p)}{1-I_I(p)},\frac{F_H(p)-F_I(p)}{1-F_I(p)}\right\rangle\middle| \ p\in P\right\}$, valid if and only if $I\geq H, T_I(p)\neq 0$, $I_I(p)\neq 1, F_I(p)\neq 1$.
- Addition: H+I= {⟨p, TH(p)+ TI(p) - TH(p)TI(p), IH(p) II(p), FH(p) FI(p) ⟩; p ∈ P}

- Multiplication: H*I= {⟨p, TH(p)TI(p) , IH(p)+II(p)- IH(p) II(p), FH(p) + FI(p)- FH(p) FI(p) ⟩; p ∈ P}.

4 | Proposed Framework

We describe the details of the proposed framework of a hybrid approach of single-valued neutrosophic sets CRITIC and MARICA methods for evaluating smart livestock framings for recommending the optimal, as shown in the following steps.

4.1 | Main Aspects Determination

Step 4.1.1. Identify n of alternatives (A_i, i = 1, 2, ..., n), which have been evaluated and compared with the other alternatives based on m of criteria (C_j,j = 1, 2, ..., m).

Step 4.1.2. Forming the panel of Decision makers.

Step 4.1.3. Constructing Neutrosophic decision matrices based on DMs' preferences by using the scale in Table 1, [32] as formed in Eq. (1).

$$X^K = \begin{array}{c} \\ \mathrm{A}_1 \\ \vdots \\ \mathrm{A_i} \\ \vdots \\ \mathrm{A_y} \end{array} \begin{array}{c} \quad C_1 \qquad\quad C_j \qquad\quad C_z \\ \begin{pmatrix} x^K{}_{11} & \cdots & x^K{}_{1j} & \cdots & x^K{}_{1z} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x^K{}_{i1} & \cdots & x^K{}_{ij} & \cdots & x^K{}_{iz} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x^K{}_{y1} & \cdots & x^K{}_{yj} & \cdots & x^K{}_{yz} \end{pmatrix} \end{array} \tag{1}$$

where $x^K{}_{ij}$ denote the evaluation of ith alternative with respect to jth criterion by expert K.

Step 4.1.4. The constructed matrices are converted to crisp matrices by using the score function [33] in Eq. (2).

$$\vartheta_{ij} = \frac{(2+\mathrm{Tr}-\mathrm{In}-\mathrm{Fl})}{3} \tag{2}$$

where ϑ_{ij} refers to the score function. whilst Tr, Fl, and In refer to truth, false, and indeterminacy respectively.

Step 4.1.5. The crisp matrices are integrated into an aggregated matrix by deploying Eq. (3).

$$x_{ij} = \frac{(\sum_{\mathrm{j=1}}^{\mathrm{Exp}} \vartheta_{ij})}{\mathrm{Exp}s} \tag{3}$$

where Exps refers to a number of experts.

4.2 | Criteria Weights Determination: CRITIC-SVN

CRITIC was proposed by Diakoulaki et al. [34] which takes into account the contradicting relationship held by each decision criterion and contrast intensity for the calculation of criteria weights.

Step 4.2.1. Normalize the aggregated decision matrix by using Eq. (4).

$$r_{ij} = \begin{cases} \dfrac{x_{ij}-\mathrm{worst}(x_j)}{\mathrm{best}(x_i)-worst(x_j)} & \text{for beneficial criteria} \quad i = 1,2,\dots,n, j = 1,2,\dots,m \\ \dfrac{x_{ij}-\mathrm{best}(x_i)}{\mathrm{worst}(x_i)-\mathrm{best}(x_i)} & \text{for non-beneficial criteria} \quad i = 1,2,\dots,n, j = 1,2,\dots,m \end{cases} \tag{4}$$

Step 4.2.2. Calculate the standard deviation for each criterion based on Eq. (5).

$$\sigma_j = \sqrt{\frac{1}{n-1} \sum_{j=1}^{n} (r_{ij} - \overline{r_j})^2} \tag{5}$$

where: $\overline{r_j}$ is the mean score of criterion j, while n is the number of alternatives.

Table 1. Single valued neutrosophic scale.

Linguistic term	CODE	Single Value Scale		
		T	I	F
Extremely Bad	EB	0.00	1.00	1.00
Very Very Bad	VVB	0.10	0.90	0.90
Very Bad	VB	0.20	0.85	0.80
Bad	B	0.30	0.75	0.70
Medium Bad	MB	0.40	0.65	0.60
Medium	M	0.50	0.50	0.50
Medium Good	MG	0.60	0.35	0.40
Good	G	0.70	0.25	0.30
Very Good	VG	0.80	0.15	0.20
Very Very Good	VVG	0.90	0.10	0.10
Extremely Good	EG	1.00	0.00	0.00

Step 4.2.3. Construct the symmetric correlation matrix by determining the correlation coefficient among criteria by formula Eq. (6).

$$C_{jk} = \sum_{i=1}^{n}(r_{ij} - r_j^{-})(r_{ij} - r_k^{-}) \Big/ \sqrt{\sum_{i=1}^{n}(r_{ij} - r_j^{-})^2 \sum_{i=1}^{n}(r_{ij} - r_k^{-})^2} \tag{6}$$

where r_j^{-} and r_k^{-} display the mean of jth and kth criteria. r_j^{-} is computed from Eq. (7).

Similarly, it is obtained for r_k^{-}: Also, C_{jk} is the correlation coefficient between jth and kth criteria

$$r_j^{-} = \frac{1}{n}\sum_{j=1}^{m} r_{ij} \quad ; \qquad i = 1,2,\ldots,n \tag{7}$$

Step 4.2.4. Determining the quantity information of criterion (IC) using Eq. (8).

$$IC_j = \sigma_j \sum_{k=1}^{m}(1 - C_{jk}) \;\; ; \; j = 1,2,\ldots,m. \tag{8}$$

where σ_j is the standard deviation of each criterion

Step 4.2.5. The weights of the criteria are determined by using Eq. (9).

$$CW_j = \frac{IC_j}{\sum_{j=1}^{m} IC_j} \tag{9}$$

4.3 | Ranking Smart Livestock Framings: MAIRCA-SVN

The principle of MAIRCA [35] is used to determine the gap(differences) between ideal and empirical weights The total gap for each noted alternative is determined by the total sum of gaps for each criterion. at last, the rank of alternative is done. An alternative with the minimum total gap value is the best one. MAIRCA is performed as follows:

Step 4.3.1. Calculating theoretical evaluation matrix (TP) through estimating preferences of alternatives through implementing Eq.(10) in the constructed aggregated matrix.

$$P_{A_j} = \frac{1}{n}; j = 1,2,\cdots,m \,; \;\; \sum_{i=1}^{n} P_{A_j}\; must\; equial\; 1 \tag{10}$$

where n is the total number of the alternatives being selected.

The elements of a matrix $R_{p_{ij}}$ is determined by the production of priority for alternatives selection and its corresponding criteria weights by Eq. (11).

$$T_{p_{ij}} = P_{A_j} \cdot CW_j ; I = 1,2,\cdots,n; j = 1,2,\cdots,m. \tag{11}$$

where CW_j weight of jth criteria.

Step 4.3.2. Establishing the real rating matrix (TR_x) as follows:

$$TR_x = \begin{array}{c} \\ \mathbf{A_1} \\ \vdots \\ \mathbf{A_i} \\ \vdots \\ \mathbf{A_n} \end{array} \begin{pmatrix} \mathbf{C_1} & \cdots \mathbf{C_j} \cdots & \mathbf{C_m} \\ rr_{x11} & \cdots rr_{x1j} \cdots & rr_{x1m} \\ \vdots & \ddots \vdots \ddots & \vdots \\ rr_{xi1} & \cdots rr_{xij} \cdots & rr_{xim} \\ \vdots & \ddots \vdots \ddots & \vdots \\ rr_{xn1} & \cdots rr_{xnj} \cdots & rr_{xnm} \end{pmatrix} ; i = 1,2,\cdots,n ; j = 1,2,\cdots,m. \tag{12}$$

where the elements of TR_x is determined by the multiplication of the theoretical rating matrix (T_p)elements by aggregated matrix.

$tr_{x_{ij}}$ denote the element at the i-th alternatives, j-th criteria determined according to the Eqs. (13) and (14):

$$tr_{x_{ij}} = T_{p_{ij}} \cdot \left(\frac{x_{ij} - Min(x_i)}{Max(x_i) - Min(x_i)}\right) \text{For the benefit type criteria} \tag{13}$$

$$tr_{x_{ij}} = T_{p_{ij}} \cdot \left(\frac{x_{ij} - Max(x_i)}{Min(x_i) - Max(x_i)}\right) \text{For the non} - \text{benefit type criteria} \tag{14}$$

Step 4.3.3. Constructing the total gap matrix (TG).

The element tg_{ij} is determined by subtracting real ratings ($rr_{x_{ij}}$)from theoretical rating ($r_{p_{ij}}$) according to Eq. (15):

$$tg_{ij=}T_{p_{ij}} - tr_{x_{ij}} \tag{15}$$

Where tg_{ij} denote gap element at i-th alternatives with respect to j-th criteria.

The final values of criteria functions $f_i$is determined by Eq. (16):

$$f_i = \sum_{i=1}^{n} tg_{ij} \tag{16}$$

Step 4.3.4. Ranking the options according to the principle that the one with the smallest f_i is the better.

5 | Application of the Proposed Hybrid Model: Smart Livestock Selection

5.1 | Problem Formulation

Livestock farming plays a critical role in our lives as it is a source of many types of foods like meat, eggs, milk, etc. With continuously increasing populations and market demands the need for food is also increased which puts pressure on farmers to solve these issues. Hence, the stakeholders attempted to mitigate these pressures by embracing the advanced technologies that support them to be competitors. As well the adoption of these technologies permits traditional livestock farms to be smarter. Thus, determining the smartest and optimal livestock farm is a complex issue. Hence, this obstacle is considered a catalyst for constructing the proposed model. Also, we need to verify and validate the accuracy of the proposed model.

Overall, we communicated with four livestock farms which embracing digital technologies in their operations and productions to contribute to the evaluation process. We are evaluating four livestock based on a set of criteria. These criteria are determined based on conducted surveys for earlier studies which related to our scope which is mentioned in Table 2.

Generally speaking, our model was implemented in four smart livestock by utilizing determined criteria as the following:

Table 2. Determined Criteria and its descriptions [20, 21].

Criteria	Goal	Description
Data collection and monitoring capabilities (C1)	Max	collect and monitor data on various aspects of livestock health, behavior, and performance. This includes sensors for monitoring vital signs, tracking movement patterns, and collecting environmental data such as temperature and humidity.
Scalability (C2)	Max	systems should be scalable to accommodate different farm sizes and types of livestock. This includes the ability to add or remove sensors, devices, or modules as needed to meet changing requirements.
Data analytics (C3)	Max	Collecting and analyzing data on various aspects of livestock farming such as feed consumption, weight gain, and environmental conditions to optimize production efficiency and animal welfare.
Disease detection and prevention (C4)	Max	Using technology such as remote sensing and AI algorithms to detect early signs of disease in livestock and implement preventive measures to minimize the spread of infections.
Drug resistance (C5)	Max	chose livestock breeds that are known for their disease resistance and overall health. This can help reduce veterinary costs and improve overall productivity.
Cost-effectiveness (C6)	Min	The cost of implementing a smart livestock farming system should be reasonable compared to the potential benefits it can provide in terms of improved productivity, efficiency, and profitability.
Data security (C7)	Max	Any data collected by the smart farming system must be secure and protected from unauthorized access or misuse.
Easy to access (C8)	Max	easy to use and maintain for farmers with varying levels of technical expertise, able to connect with other smart devices and systems to enable seamless communication and integration of data.
Waste reduction (C9)	Min	Reducing waste has a positive impact on the environment by using Fewer materials and less energy
Adaptability (C10)	Max	The smart farming system should be adaptable to changing conditions or requirements in the livestock industry, allowing for flexibility in operations.

5.2 | Analyzing and Weighting the Criteria using CRITIC based on SVN

- Three Neutrosophic decision matrices are constructed as a result of evaluation for three DMs based on the scale in Table 1 and these matrices are transformed into crisp matrices based on Eq. (2).
- Eq. (3) is employed in the crisp matrices for integrating it into an aggregated matrix as in Table 3.
- Eq. (4) is utilized in the aggregated matrix to generate a normalized matrix as in Table 4.
- The symmetric correlation matrix is constructed as in Table 5 by using Eq. (6).
- The inter-criteria correlation values for each criterion is presented in Table 6 based on Eq. (8).
- Final criteria weights are generated and obtained in Figure 1 based on Eq. (9) where C8 is the highest weight otherwise C7 is the lowest weight.

Table 3. Aggregated decision matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Live stock1	0.156	0.811	0.572	0.811	0.906	0.356	0.356	0.844	0.317	0.406
Live stock2	0.283	0.783	0.383	0.900	0.811	0.250	0.317	0.906	0.250	0.533
Live stock3	0.394	0.839	0.422	0.717	0.750	0.383	0.317	0.872	0.217	0.389
Live stock4	0.428	0.844	0.539	0.811	0.844	0.461	0.611	0.872	0.283	0.528

Table 4. Normalized matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Live stock1	0.000	0.455	1.000	0.515	1.000	0.500	0.132	0.000	1.000	0.115
Live stock2	0.469	0.000	0.000	1.000	0.393	0.000	0.000	1.000	0.333	1.000
Live stock3	0.878	0.909	0.206	0.000	0.000	0.632	0.000	0.455	0.000	0.000
Live stock4	1.000	1.000	0.824	0.515	0.607	1.000	1.000	0.455	0.667	0.962

Table 5. Correlation matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	1.000	0.658	-0.287	-0.373	-0.674	0.541	0.514	0.365	-0.600	0.292
C2	0.658	1.000	0.401	-0.798	-0.208	0.948	0.587	-0.461	-0.102	-0.288
C3	-0.287	0.401	1.000	-0.154	0.807	0.625	0.549	-0.850	0.862	-0.190
C4	-0.373	-0.798	-0.154	1.000	0.402	-0.610	0.015	0.529	0.335	0.763
C5	-0.674	-0.208	0.807	0.402	1.000	0.080	0.287	-0.558	0.994	0.080
C6	0.541	0.948	0.625	-0.610	0.080	1.000	0.774	-0.543	0.189	-0.132
C7	0.514	0.587	0.549	0.015	0.287	0.774	1.000	-0.145	0.374	0.503
C8	0.365	-0.461	-0.850	0.529	-0.558	-0.543	-0.145	1.000	-0.602	0.679
C9	-0.600	-0.102	0.862	0.335	0.994	0.189	0.374	-0.602	1.000	0.074
C 10	0.292	-0.288	-0.190	0.763	0.080	-0.132	0.503	0.679	0.074	1.000

Table 6. The inter-criteria correlation.

criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
IC	3.819	3.806	3.473	3.631	3.253	2.948	2.672	4.331	3.217	3.864

5.3 | Selecting Optimal Livestock Farm: MAIRCA based on SVN

After calculating the weights of the criteria. To evaluate and select the optimal alternative using the MARICA method as follows:

- Implementing Eq. (10) in the constructed aggregated matrix for obtaining theoretical evaluation matrix (TP) as in Table 7.
- Real rating matrix (TR_x) is calculated based on Eqs. (13) and (14) as listed in Table 8.
- To determine the total gap elements $\mathrm{tg_{ij}}$, real ratings ($\mathrm{rr_{x_{ij}}}$) is subtracting from the theoretical rating ($\mathrm{r_{p_{ij}}}$) according to Eq. (15) and results exhibited in Table 9.
- The final values of criteria functions f_i determined by Eq. (16). Figure 2 represents the ranking of livestock farms based on values of $\mathrm{f_i}$. This Figure indicated that livestock 4 is the best option followed by livestock 2 whilst livestock 1 is the worst option to choose.

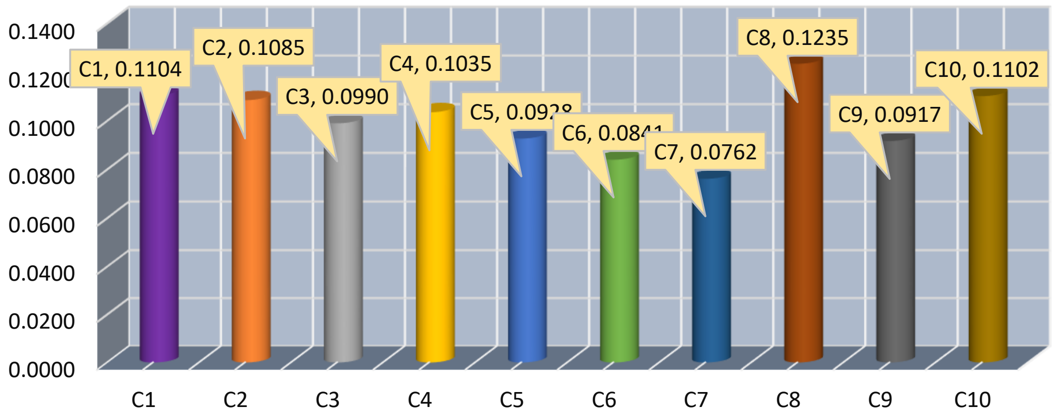

Figure 1. Criteria weights based on CRITIC-SVN.

Table 7. Theoretical ratings matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Live stock1	0.028	0.027	0.025	0.026	0.023	0.021	0.019	0.031	0.023	0.028
Live stock2	0.028	0.027	0.025	0.026	0.023	0.021	0.019	0.031	0.023	0.028
Live stock3	0.028	0.027	0.025	0.026	0.023	0.021	0.019	0.031	0.023	0.028
Live stock4	0.028	0.027	0.025	0.026	0.023	0.021	0.019	0.031	0.023	0.028

Table 8. Real ratings matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Live stock1	0.000	0.013	0.030	0.011	0.026	0.013	0.003	0.000	0.000	0.003
Live stock2	0.011	0.000	0.000	0.021	0.010	0.027	0.000	0.021	0.018	0.023
Live stock3	0.021	0.026	0.006	0.000	0.000	0.010	0.000	0.010	0.027	0.000
Live stock4	0.024	0.028	0.025	0.011	0.016	0.000	0.023	0.010	0.009	0.023

Table 9. Total gap matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Live stock1	0.028	0.015	0.000	0.013	0.000	0.011	0.017	0.031	0.023	0.024
Live stock2	0.015	0.027	0.025	0.000	0.014	0.000	0.019	0.000	0.008	0.000
Live stock3	0.003	0.002	0.020	0.026	0.023	0.013	0.019	0.017	0.000	0.028
Live stock4	0.000	0.000	0.004	0.013	0.009	0.021	0.000	0.017	0.015	0.001

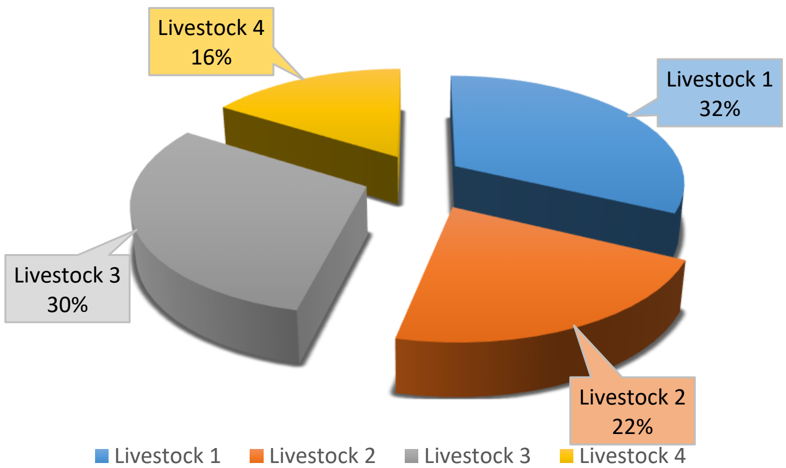

Figure 2. Ranking livestock farms based on MAIRCA based on SVN.

6 | Sensitivity and Comparative Analyses

In this section, we applied other methods for verifying our constructed model.

6.1 | Sensitivity Analysis

Firstly, we applied the sensitivity analysis method to determine the effect of changing criteria importance on the decision for final rank. Hence, we implemented six cases of changing the criteria weights which are mentioned in Table 10. The findings of six cases are formed in Figure 3. We observed that all cases agree that livestock 1 is worst and livestock 4 is optimal.

Table 10. Sensitivity analysis for criteria weights based on eleven cases.

	Case1	Case2	Case 3	Case 4	Case 5	Case 6
C1	0.1	0.125	0.075	0.075	0.075	0.075
C2	0.1	0.125	0.075	0.075	0.075	0.075
C3	0.1	0.075	0.125	0.075	0.075	0.075
C4	0.1	0.075	0.125	0.075	0.075	0.075
C5	0.1	0.075	0.075	0.125	0.075	0.075
C6	0.1	0.075	0.075	0.125	0.075	0.075
C7	0.1	0.075	0.075	0.075	0.125	0.075
C8	0.1	0.075	0.075	0.075	0.125	0.075
C9	0.1	0.075	0.075	0.075	0.075	0.125
C10	0.1	0.075	0.075	0.075	0.075	0.125

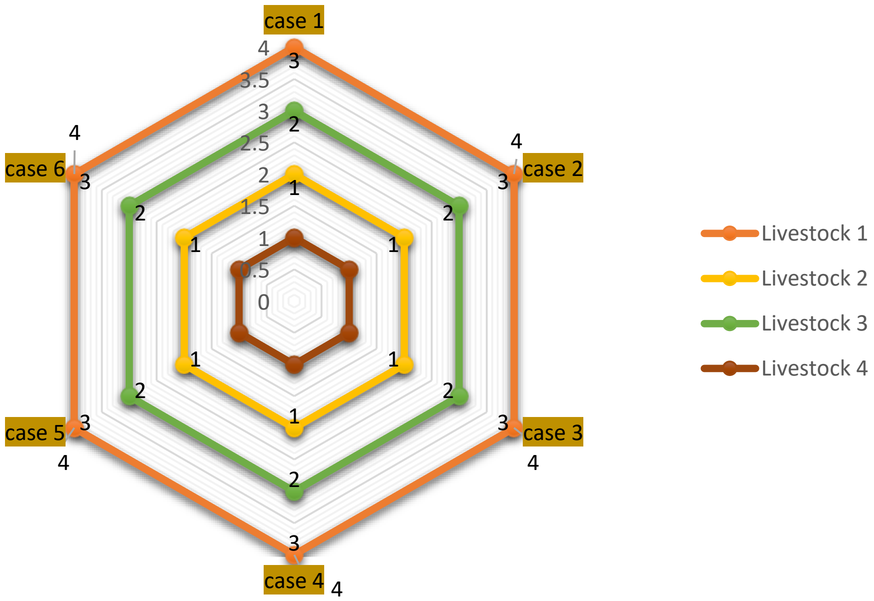

Figure 3. Various rankings for livestock farms based on sensitivity analysis.

6.2 | Comparative Analysis

Firstly, our model is compared with the WSM method [36]where the order of ranking is A4 > A3 > A2 >A1. Then, our model is compared with another MCDM method is MABAC method [37] and findings indicated that the order of ranking is A4 > A2 > A3 >A1.

From the above-detailed analysis, the three models give the same optimal alternative A4 and the same worst one A1. This verifies the SVNN-MARICA is reasonable and effective.

Table 11. Evaluation results according to different methods.

Methods	Order	Best alternative	Worst alternative
SVNN-MARICA	A4 > A2 > A3 >A1	A4	A1
SVNN-WSM	A4 > A2 > A3 >A1	A4	A1
SVNN-MABAC	A4 > A2 > A3 >A1	A4	A1

7 | Conclusion

This study illustrates the impact of New Technologies such as IoT, blockchain, and digital twins on traditional livestock farming to be smart. Moreover, presents a single-valued neutrosophic-based model for selecting the best livestock farming. In this paper, four smart livestock were compared based on eight beneficial criteria and two costs to select the best one. The SVNs were used to handle vague and incomplete data then the CRITIC method was used to determine criteria weights followed by the MARICA MCDM method to identify the best smart livestock farming. The proposed model and its findings were validated via a sensitivity analysis. This study compared the proposed model with two different MCDM methods called WSM, and MABAC. Results of the comparison show that the three methods agreed on the same best and worst alternative.

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Author Contribution

All authors contributed equally to this work.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

References

[1] Muhammad Irfan Said, "The Role of the Livestock Farming Industry in Supporting the Global Agricultural Industry," in Agricultural Development in Asia, Md. Asaduzzaman and Mafruha Afroz, Eds., Rijeka: IntechOpen, 2021, p. Ch. 7. doi: 10.5772/intechopen.97868.

[2] K. A. Saravanan, M. Panigrahi, H. Kumar, B. Bhushan, T. Dutt, and B. P. Mishra, "Selection signatures in livestock genome: A review of concepts, approaches and applications," Livest. Sci., vol. 241, p. 104257, Nov. 2020, doi: 10.1016/j.livsci.2020.104257.

[3] E. Vranken and D. Berckmans, "Precision livestock farming for pigs," Anim. Front., vol. 7, no. 1, pp. 32–37, Jan. 2017, doi: 10.2527/af.2017.0106.

[4] S. -K. Jo, D. -H. Park, H. Park, and S. -H. Kim, "Smart Livestock Farms Using Digital Twin: Feasibility Study," in 2018 International Conference on Information and Communication Technology Convergence (ICTC), Oct. 2018, pp. 1461–1463. doi: 10.1109/ICTC.2018.8539516.

[5] C. Bahlo, P. Dahlhaus, H. Thompson, and M. Trotter, "The role of interoperable data standards in precision livestock farming in extensive livestock systems: A review," Comput. Electron. Agric., vol. 156, pp. 459–466, Jan. 2019, doi: 10.1016/j.compag.2018.12.007.

[6] H. Taherdoost and M. Madanchian, "Multi-Criteria Decision Making (MCDM) Methods and Concepts," Encyclopedia, vol. 3, no. 1, pp. 77–87, 2023, doi: 10.3390/encyclopedia3010006.

[7] X. Sun and Y. Li, An Intelligent Multi-Criteria Decision Support System for Systems Design, vol. 51. 2010. doi: 10.2514/1.C032296.

[8] P. K. Singh, "Uncertainty analysis in document publications using single-valued neutrosophic set and collaborative entropy," Artif. Intell. Rev., vol. 56, no. 3, pp. 2785–2809, Mar. 2023, doi: 10.1007/s10462-022-10249-7.

[9] S. Pramanik, "Single-Valued Neutrosophic Set: An Overview," in Transdisciplinarity, N. Rezaei, Ed., Cham: Springer International Publishing, 2022, pp. 563–608. doi: 10.1007/978-3-030-94651-7_26.

[10] M. S. Farooq, O. O. Sohail, A. Abid, and S. Rasheed, "A Survey on the Role of IoT in Agriculture for the Implementation of Smart Livestock Environment," IEEE Access, vol. 10, pp. 9483–9505, 2022, doi: 10.1109/ACCESS.2022.3142848.

[11] Q. M. Ilyas and M. Ahmad, "Smart Farming: An Enhanced Pursuit of Sustainable Remote Livestock Tracking and Geofencing Using IoT and GPRS," Wirel. Commun. Mob. Comput., vol. 2020, p. 6660733, Dec. 2020, doi: 10.1155/2020/6660733.

[12] V. Rana, S. Sharma, K. THAKUR, A. Pandit, and S. Mahajan, Internet of Things in Livestock Farming: Implementation and Challenges. 2023. doi: 10.21203/rs.3.rs-2559126/v1.

[13] L. Germani, V. Mecarelli, G. Baruffa, L. Rugini, and F. Frescura, "An IoT Architecture for Continuous Livestock Monitoring Using LoRa LPWAN," Electronics, vol. 8, no. 12, 2019, doi: 10.3390/electronics8121435.

[14] P. Rajak, A. Ganguly, S. Adhikary, and S. Bhattacharya, "Internet of Things and smart sensors in agriculture: Scopes and challenges," J. Agric. Food Res., vol. 14, p. 100776, Dec. 2023, doi: 10.1016/j.jafr.2023.100776.

[15] K. Dineva and T. Atanasova, "Design of Scalable IoT Architecture Based on AWS for Smart Livestock," Animals, vol. 11, no. 9, 2021, doi: 10.3390/ani11092697.

[16] R. S. Alonso, I. Sittón-Candanedo, Ó. García, J. Prieto, and S. Rodríguez-González, "An intelligent Edge-IoT platform for monitoring livestock and crops in a dairy farming scenario," Ad Hoc Netw., vol. 98, p. 102047, Mar. 2020, doi: 10.1016/j.adhoc.2019.102047.

[17] N. Radziwill, "Blockchain Revolution: How the Technology Behind Bitcoin is Changing Money, Business, and the World.," Qual. Manag. J., vol. 25, no. 1, pp. 64–65, Jan. 2018, doi: 10.1080/10686967.2018.1404373.

[18] A. S. Patel, M. N. Brahmbhatt, A. R. Bariya, J. B. Nayak, and V. K. Singh, "'Blockchain technology in food safety and traceability concern to livestock products,"' Heliyon, vol. 9, no. 6, p. e16526, Jun. 2023, doi: 10.1016/j.heliyon.2023.e16526.

[19] S. Awan, "Role of Internet of Things (IoT) with Blockchain Technology for the Development of Smart Farming," J. Mech. Contin. Math. Sci., vol. 14, Oct. 2019, doi: 10.26782/jmcms.2019.10.00014.

[20] S. Neethirajan and B. Kemp, Digital Twins in Livestock Farming. 2021. doi: 10.20944/preprints202101.0620.v1.

[21] Dr. M. Alshehri, "Blockchain-assisted internet of things framework in smart livestock farming," Internet Things, vol. 22, p. 100739, Jul. 2023, doi: 10.1016/j.iot.2023.100739.

[22] N. A. Natraj, S. Balasubaramanian, K. B. Gurumoorthy, A. Purushothaman, and P. Kannan, "Empowering Agriculture: Blockchain's Revolution in Smart Farming," in Intelligent Robots and Drones for Precision Agriculture, S. Balasubramanian, G. Natarajan, and P. R. Chelliah, Eds., Cham: Springer Nature Switzerland, 2024, pp. 207–240. doi: 10.1007/978-3-031-51195-0_11.

[23] C. Pylianidis, S. Osinga, and I. N. Athanasiadis, "Introducing digital twins to agriculture," Comput. Electron. Agric., vol. 184, p. 105942, May 2021, doi: 10.1016/j.compag.2020.105942.

[24] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital Twin in Industry: State-of-the-Art," IEEE Trans. Ind. Inform., vol. 15, no. 4, pp. 2405–2415, Apr. 2019, doi: 10.1109/TII.2018.2873186.

[25] N. Peladarinos, D. Piromalis, V. Cheimaras, E. Tserepas, R. A. Munteanu, and P. Papageorgas, "Enhancing Smart Agriculture by Implementing Digital Twins: A Comprehensive Review," Sensors, vol. 23, no. 16, 2023, doi: 10.3390/s23167128.

[26] [26] S. Cesco, P. Sambo, M. Borin, B. Basso, G. Orzes, and F. Mazzetto, "Smart agriculture and digital twins: Applications and challenges in a vision of sustainability," Eur. J. Agron., vol. 146, p. 126809, May 2023, doi: 10.1016/j.eja.2023.126809.

[27] C. Verdouw, B. Tekinerdogan, A. Beulens, and S. Wolfert, "Digital twins in smart farming," Agric. Syst., vol. 189, p. 103046, Apr. 2021, doi: 10.1016/j.agsy.2020.103046.

[28] C. Verdouw, "Virtualization of Smart Farming with Digital Twins," in Encyclopedia of Smart Agriculture Technologies, Q. Zhang, Ed., Cham: Springer International Publishing, 2022, pp. 1–9. doi: 10.1007/978-3-030-89123-7_146-1.

[29] W. Purcell and T. Neubauer, "Digital Twins in Agriculture: A State-of-the-art review," Smart Agric. Technol., vol. 3, p. 100094, Feb. 2023, doi: 10.1016/j.atech.2022.100094.

[30] M. Abdel-Basset and M. Mohamed, "Role of Single Valued Neutrosophic Set and Rough Set in Smart City: Imperfect and Incomplete Information System," Measurement, vol. 124, Apr. 2018.

[31] F. Smarandache, "Neutrosophic Probability, Set, And Logic (first version)," Jan. 2000, doi: 10.5281/zenodo.57726.
[32] M. Abdel-Basset, A. Gamal, N. Moustafa, A. Abdel-Monem, and N. El-Saber, "A Security-by-Design Decision-Making Model for Risk Management in Autonomous Vehicles," IEEE Access, vol. 9, pp. 107657–107679, 2021, doi: 10.1109/ACCESS.2021.3098675.
[33] X. Peng and J. Dai, "Approaches to single-valued neutrosophic MADM based on MABAC, TOPSIS and new similarity measure with score function," Neural Comput. Appl., vol. 29, no. 10, pp. 939–954, May 2018, doi: 10.1007/s00521-016-2607-y.
[34] D. Diakoulaki, G. Mavrotas, and L. Papayannakis, "Determining objective weights in multiple criteria problems: The critic method," Comput. Oper. Res., vol. 22, no. 7, pp. 763–770, Aug. 1995, doi: 10.1016/0305-0548(94)00059-H.
[35] I. Badi and M. Ballem, "Supplier Selection using Rough BWM-MAIRCA model: A case study in Pharmaceutical Supplying in Libya," Decis. Mak. Appl. Manag. Eng., vol. 1, pp. 2560–6018, Jun. 2018, doi: 10.31181/dmame1802016b.
[36] E. Mulliner, N. Malys, and V. Maliene, "Comparative analysis of MCDM methods for the assessment of sustainable housing affordability," Omega, vol. 59, pp. 146–156, Mar. 2016, doi: 10.1016/j.omega.2015.05.013.
[37] A. Torkayesh, E. Babaee Tirkolaee, A. Bahrini, D. Pamucar, and A. Khakbaz, "A Systematic Literature Review of MABAC Method and Applications: An Outlook for Sustainability and Circularity," Informatica, pp. 1–34, Feb. 2023, doi: 10.15388/23-INFOR511.