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Automated Livestock Practices: Incorporation Emerging Contemporary Technologies Toward Sustainable Livestock in Era of Smart Cities

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Abstract

Currently, numerous spheres now face a wider range of needs due to the increasingly competitive and globalized global market. Moreover, digital technologies are necessary for analysis and comprehension in many sectors of contemporary society. For instance, Internet of Things (IoT) has the potential to revolutionize livestock management, including the dairy cattle industry, by providing real-time data and enabling data-driven decisions to improve animal welfare, increase productivity, and promote sustainable farming practices. The main components of IoT-enabled livestock management include sensors, communication systems, data storage, and analysis systems. These components of IoT-enabled livestock management improve animal welfare, increase productivity, and reduce environmental impact. As well as promoting sustainable farming practices through using of precision farming methods, early illness detection, prevention, and improved animal reproduction and breeding. Given the importance of leveraging IoT in livestock, this study examines and categorizes IoTs' applications based on their functionalities and objectives. Thus, this process has been conducted by identifying criteria or factors that are important for evaluating the effectiveness of IoT applications. To serve the study's objectives, we are harnessing various techniques. Firstly, we are modeling the identified IoTs applications' criteria into levels that encompass a set of nodes by utilizing Tree Soft Technique (TrST). Secondly, Multi-Criteria Decision Making (MCDM) techniques are utilized for certain roles as criteria importance through inter-criteria correlation (CRITIC) for analyzing identified criteria and determining weights for them. These weights are leveraged in another technique of MCDM in this study for ranking IoT applications entailed in TOmada de Decisao Interativa Multicriterio (TODIM). The utilized techniques operate within the sovereignty of neutrosophic theory for supporting these techniques in uncertain situations and when treated with incomplete data.

Keywords: livestock Management; Internet of Things (IoT); Tree Soft Technique (TrST); Multi-Criteria Decision Making (MCDM); Neutrosophic Theory.

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1 | Introduction

Livestock refers to domesticated animals raised in an agricultural setting for various purposes, including food production, fiber, labor, and companionship. Livestock can encompass a wide range of animals, each serving different roles and providing various products for human consumption and other uses[1].

Livestock plays a crucial role in global food security, providing a significant source of protein, essential nutrients, and economic livelihoods for millions of people worldwide. Damian Maye proposes a framework for achieving sustainable food security in smart cities. The framework involves integrating food systems into the urban planning process and using technology to optimize food production, distribution, and consumption [2]. The increasing demand for animal protein and the need for sustainable agriculture have led to the adoption of advanced technologies in livestock management. The Internet of Things (IoT) and Artificial Intelligence (AI) are two such technologies that have revolutionized the way farmers manage their livestock [3].

Livestock management in a smart city context involves integrating IoT technologies and data analytics to optimize the care, health, and productivity of livestock within urban environments[4]. Livestock management in a smart city context can be significantly improved with the use of advanced technologies. The evidence of this [5] where IoT sensors are utilized for remote monitoring of the location, well-being, and health of the livestock. Also, these sensors can be assigned to individual cattle and can collect data in real time, enabling farmers to monitor and manage their livestock remotely. In the same vein [6] indicated that leveraging Information and Communication Technologies (ICT) as digital innovation is achieving productivity growth resources in the field of agriculture and animal husbandry. The use of precision agriculture techniques, smart sensors, and livestock monitoring solutions can also help farmers improve traceability and increase the overall productivity of their farms. By collecting and analyzing data from various locations around the livestock houses, farmers can identify patterns and make informed decisions to improve productivity, reduce costs, and ensure animal welfare. In the context of smart cities, livestock farming can benefit from the integration of advanced technologies and IoT solutions. These technologies can help farmers to manage resources and improve productivity, while also enhancing animal welfare [7] more efficiently. For instance, sensors can be used to monitor ammonia levels, which can cause respiratory problems in animals and humans, and help farmers keep these levels under control [8]. Rajneesh Thakur et.al discusses the potential of digital technologies in revolutionizing livestock farming. These digital technologies include IoT, AI, blockchain (BC), and big data [9].

IoT plays a crucial role in the development of smart cities. It involves the use of various digital devices such as smart sensors, monitoring devices, AI programs, and actuators that interact and communicate with each other to affect different aspects of city life. With IoTs, cities can become more efficient, sustainable, and livable [10]. IoTs technology enables farmers to monitor the health, behavior, and environmental conditions of their livestock in real time. Through wearable sensors, farmers can track various parameters such as temperature, humidity, and movement, which can help them identify potential health issues at an early stage. IoT devices can also be used to monitor the quality and quantity of food and water consumed by the animals, ensuring that they receive the right nutrition. According to [11] some of the key IoT technologies that are being used in livestock farming are Wireless sensor networks (WSNs) for monitoring environmental conditions, animal behavior, and physiological parameters. Also, Radio-frequency identification (RFID) in [12] is utilized for tracking and identifying individual animals. Shao et al. [13] mentioned other technologies such as Global Positioning System (GPS) technology for tracking the location of animals and vehicles Drone and unmanned aerial vehicle (UAV) systems for monitoring and managing large parcels of land. These technologies in [14] as Automated feeding and watering systems for improving animal health and reducing labor costs. The use of GPS, RFID, and other technologies for automated tracking of individual animals. These technologies can be used to monitor and evaluate animal welfare [15]. Wataru Iwasaki et. al introduces some representative IoT sensors for livestock monitoring, including both commercialized models and prototypes in research stages, and evaluates their strengths and weaknesses [16]. According to the research paper "Optimization of Livestock Monitoring System in Outdoor Based on IoTs" by Andi Chairunnas and

Agung Prajuhana Putra an IoT-based livestock monitoring system can help farmers remotely monitor and manage their livestock's health, feeding, and behavior, leading to improved productivity, profitability, and sustainability [17].

According to a systematic literature review published in 2022 [18] stated that IoT is increasingly being used in agriculture, including in the implementation of livestock farming. In addition, artificial intelligence and machine learning can be used to analyze the data collected from the sensors and predict trends, identify potential issues, and provide insights to improve the overall management of the livestock.

IoT sensors can monitor air and water quality, noise levels, and other environmental parameters. By collecting and analyzing this data, cities can take proactive measures to mitigate pollution, prevent environmental degradation, and protect public health. Sang-O Park [19] suggested that climate-smart livestock systems can help mitigate the livestock crisis caused by climate change and maintain sustainable livestock production and concluded that the development of sustainable livestock production systems with farm animal algorithms is essential to address the challenges of climate change in the future. Aden Giro aims to reduce greenhouse gas emissions while improving livestock productivity and resilience and discusses several strategies and approaches to achieve these goals, including sustainable feed and water management, improved genetics, and the use of innovative technologies [20].

Due to the significance of IoTs, particularly in smart cities for livestock as previously declared. This study constructed a decision-making framework for evaluating the role of IoTs in livestock by analyzing IoT applications and ranking it through applying TrST which was introduced by Smarandache [21], MCDM techniques, and Neutrosophic theory which was also, proposed by Smarandache.

The main contributions of this study are exhibited in the following points:

- Showcases the role of digital technologies especially, IoTs in livestock through conducting surveys for prior studies.
- Determining the influenced criteria and sub-criteria of IoTs applications and modeling it into tress structure.
- Weighting these nodes (i.e. criteria and sub-criteria) of the tree using CRITIC and utilizing these weights into TODIM to rank IoT applications. These techniques operate based on single-valued triangular Neutrosophic sets (SVTrNSs).
- Applying the constructed decision-making framework in a real case study to verify that the constructed framework is acceptable.

2 | Comprehensive Study

This section included the comprehensive study for utilized techniques in our study in the field of evaluation as follows.

2.1 | Evaluation process based on the CRITIC method

The CRITIC (CRiteria Importance Through Intercriteria Correlation) method is MCDM technique that aims to determine the relative importance of criteria by analyzing their Intercriteria correlations. The method was developed by Diakoulaki, Mavrotas, and Papathanasiou in the early 1990s [22]. The CRITIC method is based on the fact that the criteria of a decision-making problem are often interconnected and correlated, and the relative importance of each criterion should be determined based on its inter-criteria correlations. The CRITIC method has been applied in the context of IoT for estimating the objective weights of decision criteria. In a study by Anath Rau Krishnan et.al [23]. proposed a modified CRITIC method for evaluating the relative importance of decision criteria for IoTs-based wireless mesh networks. The modified CRITIC method is based on the entropy of the criteria, the correlation between criteria, and the standard deviation of the criteria. The results of the study showed that the proposed method is effective in determining the weights of decision criteria and can be used for decision-making in IoT systems. A comprehensive evaluation approach for efficient countermeasure techniques against timing side-channel attacks (TSCA) on MPSoC-based IoT systems using multi-criteria decision-making methods involves a Fermatean-FDOSM framework for ranking and the CRITIC technique for criteria weighting [24]. The proposed approach evaluates techniques for countering denial-of-service (DoS) attacks on MPSoC-based IoT systems using a Fermatean-FDOSM framework for ranking and a CRITIC technique for criteria weighting [25]. Implementing the MCDM Fuzzy Neutrosophic TOPSIS-CRITIC approach for determining sustainability aspects of an IoTs-based product warehouse location involves the following steps. The implementation of this approach can help decision-makers in selecting the most sustainable warehouse location for an IoTs-based product warehouse by comprehensively considering the impact on multiple criteria [26].

2.2 | Evaluation process based on the TODIM method

TODIM is clarified by [27] as an acronym for the Portuguese "TOMADIM de decisão multicritério", which translates to "Interactive and Multi-criteria Decision Making". This method was developed by Gomes and Lima-based on the prospect theory [28], which takes into account the risk attitudes of decision-makers. The objective of this method is to analyze rank alternatives based on a set of criteria, using a value function that reflects the dominance of one alternative over another. It is widely used in various fields, such as management, economics, and engineering, to solve multi-criteria decision-making problems [29]. Ke Zhang et.al presents a novel method for solving group decision-making (GDM) problems with Interval-valued Multiplicative Preference Relations (IMPRs) using the Stochastic Group Preference Acceptability Analysis with TODIM (SGPAA-TODIM) method [30]. Yushuo et al. proposed a framework of Fuzzy-TODIM [31] for evaluating food waste treatment techniques. Zeyuan et.al [32] presented a new method called CPT-TODIM-CDMT for green supplier selection using Type-2 Neutrosophic Numbers (T2NN). The method used a new distance measure called cosine distance measure for T2NN (CDMT) applied to the TODIM method. Mehdi et.al [33] proposed a decision-making method based on the TODIM approach in a hyperbolic fuzzy environment. This method addressed the subjectivity in the construction of the decision matrix by proposing a systematic approach based on the Kano model.

3 | Material and Methods

This section illustrated the basic concept of utilized techniques. It also exhibited the methodology of implementing these techniques for constructing decision-making. Hence, this section is divided into two sub-sections as follows.

3.1 | Preliminaries

3.1.1| Tree Soft Technique

Smarandache [21] proposed TrST as well as Neutrosophic theory. The concept of TrST is described based on the following points:

Let U be a universe of discourse, and $\mathcal{H}$ a non-empty and subset of U, whilst the powerset of $\mathcal{H}$ denoted as P($\mathcal{H}$).

The main level has main attributes/criteria/factors and is symbolled as T. Accordingly, T has a set of T_s with (one-digit indexes) = $\{T_1, T_2, \ldots T_n\}$.

Level 2 has sub-criteria or other word sub-nodes that have two-digit indexes and are symbolled as:

$\{T_{11},.. T_{1n}\}$ are sub-nodes of T_1 , $\{T_{21},.. T_{2n}\}$ are sub-nodes of T_2 , and $\{T_{31},.. T_{3n}\}$ are sub-nodes of T_3

Generally, a graph tree is formed, which we denote as Tree(Y), whose root is considered of level zero, We call the leaves of the graph-tree, all terminal nodes (nodes that have no descendants). Hence, TreeSoft Set is F: P(Tree(Y)) → P($\mathcal{H}$).

All node sets of TreeSoft Set of level m are: Tree(Y) = {Yi1 | i1= 1, 2, ... }

3.1.2 | Single Value Triangular Neutrosophic Sets(SVTNSs)

In this section, we present the basic concepts of SVTrNSs [34] as

$\widetilde{\mathrm{Ne}} = (\ell, \mathcal{M}, \mho); \vartheta_{\widetilde{\mathrm{Ne}}}\ , \theta_{\widetilde{\mathrm{Ne}}}, \sigma_{\widetilde{\mathrm{Ne}}}$, where $\ell, \mathcal{M}, \mho$ are the lower, middle, and upper parts of neutrosophic. While SVTrNS is represented as a triplet (ϑ, θ, σ), where ϑ is the membership degree, θ is the indeterminacy degree, and σ is the non-membership degree.

-Let $\widetilde{\mathrm{Ne}} =< (\ell, \mathcal{M}, \mho); \vartheta_{\widetilde{\mathrm{Ne}}}\ , \theta_{\widetilde{\mathrm{Ne}}}, \sigma_{\widetilde{\mathrm{Ne}}} >$ is a neutrosophic set on the real line set $\mathfrak{R}$. a set is classified into membership function as truth-membership function ($\vartheta_{\widetilde{Ne}}$), indeterminacy membership function ($\theta_{\widetilde{Ne}}$) and falsity membership function ($\sigma_{\widetilde{Ne}}$) and the equation formed these memberships as follows:

[35]:

$T_{\widetilde{Ne}}$ represents the degree of truth that element x belongs to the neutrosophic set.

$$T_{\widetilde{Ne}} = \begin{cases} \vartheta_{\widetilde{Ne}} \left(\frac{x-\ell}{\mathcal{M}-\ell}\right) & \ell \leq x \leq \mathcal{M} \\ \vartheta_{\widetilde{Ne}} & x = \mathcal{M} \\ \vartheta_{\widetilde{Ne}} \left(\frac{\mho-x}{\mho-\mathcal{M}}\right) & \mathcal{M} \leq x \leq \mho \\ 0 & otherwise \end{cases} \tag{1}$$

$I_{\widetilde{Ne}}$ represents the degree of uncertainty or ambiguity that the element x belongs to the neutrosophic set.

$$I_{\widetilde{Ne}} = \begin{cases} \theta_{\widetilde{Ne}} \left(\frac{\mathcal{M}-x}{\mathcal{M}-\&\ell}\right) & \ell \leq x \leq \mathcal{M} \\ \theta_{\widetilde{Ne}} & x = \mathcal{M} \\ \theta_{\widetilde{Ne}} \left(\frac{x-\mho}{\mho-\mathcal{M}}\right) & \mathcal{M} \leq x \leq \mho \\ 1 & otherwise \end{cases} \tag{2}$$

$F_{\widetilde{Ne}}$ represents the degree of falsity that the element x belongs to the neutrosophic set.

$$F_{\widetilde{Ne}} = \begin{cases} \sigma_{\widetilde{Ne}} \left(\frac{\mathcal{M}-x}{\mathcal{M}-\ell}\right) & \ell \leq x \leq \mathcal{M} \\ \sigma_{\widetilde{Ne}} & x = \mathcal{M} \\ \sigma_{\widetilde{Ne}} \left(\frac{x-\mho}{\mho-\mathcal{M}}\right) & \ell \leq x \leq \mho \\ 1 & otherwise \end{cases} \tag{3}$$

Score Function to convert to crisp or de-neutrosophic numbers

$$S(r_{ij}) = \frac{(\ell_{ij}+\mathcal{M}_{ij}+\mho_{ij})}{9} * (2 + \vartheta - \theta - \sigma) \tag{4}$$

3.2 | Methodology of evaluating of IoT applications

The evaluation process for IoT applications is described according to the following steps.

Step 1: Utilization of TrST for forming a tree of criteria and sub-criteria.

Determining the criteria and sub-criteria related to utilizing IoTs in livestock.

Forming these criteria and sub-criteria into nodes of levels.

Communicating with expert panel for evaluating IoT applications based on nodes in levels of tree.

Step 2: Analyzing and evaluating criteria and sub-criteria formed into TrST using the CRITIC method [26]:

Neutrosophic matrices based on the rating of the expert panel are constructed.

Deneutrosophic these matrices using Eq. (4) and aggregated these matrices into an aggregated matrix according to Eq. (5).

$$x_{ij} = \frac{\sum_{ex=1}^{ex} r_{ij}}{M} \tag{5}$$

Where: M is the number of members of the expert panel

Compute the normalized decision matrix using Eq. (6).

$$\overline{x_{ij}} == \frac{x_{ij} - x_i^{worst}}{x_i^{best} - x_i^{worst}} \quad \text{i = 1; . . .; m; j = 1; . . .; n} \tag{6}$$

where $\overline{X_{ij}}$ represents a normalized value of the decision matrix for ith alternative in the jth attribute

Calculate the standard deviation (STDEV) for each criterion per column according to

$$\sigma_j = \sqrt{\frac{1}{n-1} \sum_{j=1}^{n} (x_{ij} - \bar{X}_j)^2} \tag{7}$$

Where: $\bar{x}_j$ is the mean score of criterion j, while n is the number of alternatives.

Compute the linear correlation coefficient between criteria values by

$$P_{jk} = \sum_{i=1}^{m} (x_{ij} - \bar{x}_j)\,(x_{ik} - \overline{x_k}) / \sqrt{\sum_{i=1}^{m} (x_{ij} - \bar{x}_j)^2 \sum_{i=1}^{m} ((x_{ik} - \overline{x_k})^2} \tag{8}$$

where $\bar{x}_j$ and $\overline{x_k}$ display the mean of jth and kth attributes. $\bar{x}_j$ is computed from Eq. (9). Similarly, it is obtained for $\bar{x_k}$ Also, P_{jk} is the correlation coefficient between the jth and kth criteria.

$$\bar{x}_j = \frac{1}{n} \sum_{j=1}^{n} x_{ij} \tag{9}$$

The index is calculated by

$$C_j = \sigma_j \sum_{k=1}^{n} (1 - P_{jk}) \tag{10}$$

The final weight is calculated by

$$w_j = \frac{c_j}{\sum_{j=1}^{n} c_j} \tag{11}$$

Step 3: Ranking IoT applications using the TODIM method [30]:

TODIM based on SVTrNSs are employed for ranking alternatives based on weights generalized from CRITIC these steps are applied:

Normalize the aggregated matrix constructed from the previous step as follows:

$$\mathcal{P}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad \text{for beneficial} \tag{12}$$

$$\mathcal{P}_{ij} = \frac{{}^{1}/_{x_{ij}}}{\sum_{i=1}^{m} {}^{1}/_{x_{ij}}} \quad \text{for non-beneficial} \tag{13}$$

Determine the relative weight using weights obtained from CRITIC using Eq. (14).

$$\breve{W}_j = \frac{w_j}{\breve{w}} \tag{14}$$

Where $\breve{\mathcal{W}}$ the maximum amount of the weights.

Calculate the dominance degree of the alternative as following Eq.s:

$$\delta(\mathcal{A}_i, \mathcal{A}_j) = \sum_{j=1}^{m} \Phi\left(\mathcal{A}_i, \mathcal{A}_j\right) \tag{15}$$

$$\Phi\left(\mathcal{A}_i, \mathcal{A}_j\right) = \begin{cases} \sqrt{\frac{\mathcal{W}_j\,(\mathcal{P}_i - \mathcal{P}_j)}{\sum_{j=1}^{n} \breve{\mathcal{W}}_j}} & if\ \left(\mathcal{P}_i - \mathcal{P}_j\right) > 0 \\ 0 & if\ \left(\mathcal{P}_i - \mathcal{P}_j\right) = 0 \\ \frac{-1}{\theta}\sqrt{\frac{\sum_{j=1}^{n} \breve{\mathcal{W}}_j\,(\mathcal{P}_i - \mathcal{P}_j)}{\mathcal{W}_j}} & if\ \left(\mathcal{P}_i - \mathcal{P}_j\right) < 0 \end{cases} \tag{16}$$

Where $\boldsymbol{\theta}$ the attenuation factor of the losses value ranges from 1 to 10.

Calculate the overall dominance degree of each alternative using this Eq.:

$$\boldsymbol{\zeta_i} = \frac{\sum_{j=1}^{n} \delta(\mathcal{A}_i, \mathcal{A}_j) - \min \sum_{j=1}^{n} \delta(\mathcal{A}_i, \mathcal{A}_j)}{\max \sum_{j=1}^{n} \delta(\mathcal{A}_i, \mathcal{A}_j) - \min \sum_{j=1}^{n} \delta(\mathcal{A}_i, \mathcal{A}_j)} \tag{17}$$

Finally, rank all alternatives based on the value of the overall dominance degree.

4 | Application

Herein, we are implementing the constructed model in a real case study to validate the accuracy of our constructed model.

Problem Description:

4.1 | Problem Description

IoTs in livestock management is a technology that involves the use of sensors to monitor various aspects of livestock management, such as the health, behavior, and environment of the animals. By using IoTs-enabled livestock management, farmers can collect real-time data and make data-driven decisions to improve animal welfare, increase productivity, and promote sustainable farming practices. Also, monitoring key environmental factors such as temperature, humidity, and air quality, as well as the monitoring of animal vital signs, behavior, and feeding patterns. Moreover, early illness detection and prevention, and improved animal reproduction and breeding can contribute to more profitable and sustainable farming practices.

4.2 | Definition of alternatives and criteria

Herein, we are evaluating IoT applications as alternatives in the dairy cattle industry by using MCDM methods.

Alt1: Premature Disease Detection [36]: Early detection of diseases is crucial for preventing outbreaks and minimizing the spread of illness within the herd. IoTs-based health monitoring systems, such as wearable sensors or smart collars, can continuously monitor vital signs and behavior patterns of cattle to detect early signs of illness. By promptly identifying sick animals, farmers can implement appropriate interventions, such as isolation, treatment, or vaccination, to prevent further spread and minimize economic losses.

Alt2: Estimating the timing of calving [37]: Accurately predicting the timing of calving allows farmers to provide appropriate care and supervision to ensure a successful birthing process and improve calf survival rates. IoT devices, such as smart calving sensors or predictive analytics algorithms, can monitor physiological indicators and behavioral changes in pregnant cows to estimate the timing of parturition. Early warning alerts can help farmers prepare for the upcoming calving event by ensuring the availability of assistance, clean bedding, and necessary veterinary support.

Alt3: Estimating the Insemination Period [38]: Timely insemination of dairy cows during their estrus cycle is essential for maximizing breeding efficiency and reproductive success. IoT-based estrus detection systems, such as activity monitors or behavior-tracking devices, can accurately identify the onset of estrus and predict the optimal timing for artificial insemination.

Alt4: Locate and Identify the Dairy Cattle: Efficient tracking and management of individual dairy cattle are essential for monitoring herd health, optimizing feeding practices, and ensuring proper animal welfare. IoTs-based solutions, such as RFID ear tags or GPS-enabled collars, can provide real-time location tracking and unique identification of each animal within the herd.

4.3 | Decision-making and experimental results

4.3.1 | Identifying criteria and sub-criteria of IoTs application and forming into Tree form

Figure 1 showcases the structure of influenced criteria and sub-criteria in Tree form.

The expert panel rates the IoT applications based on influenced criteria and sub-criteria in Tree form by utilizing the scale of SVTrNSs as used in [39].

4.3.2 | Valuation criteria and sub-criteria formed in Tree using SVTrNS-CRITIC

For the First Level

First build a decision matrix using single-valued triangular neutrosophic numbers as we have 3 decision-makers each expressing his opinions by using the triangular neutrosophic scale.

using Eq. (4) to de-neutrosophic these matrices then the aggregated decision matrix is calculated by Eq. (5) and represented in Table 1.

By Eq. (6) normalized matrix is calculated and shown in Table 2.

The correlation coefficients for the main criteria and final weights are shown in Table 3.

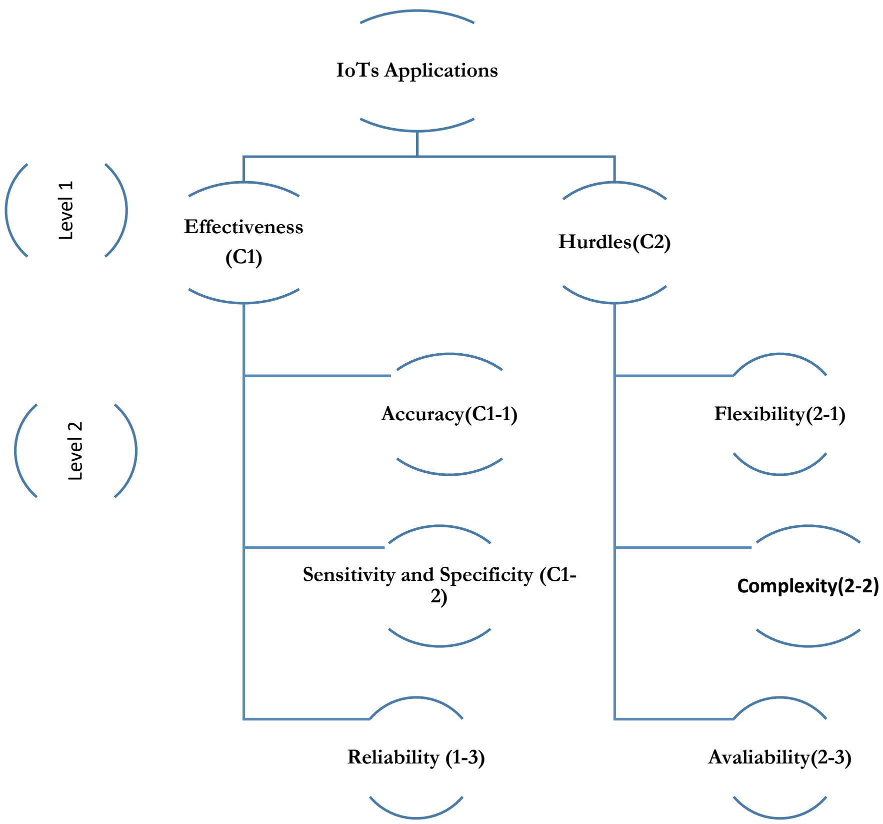

Figure 1. Forming criteria and sub-criteria into levels of Tree Soft.

Table 1. Aggregated matrix.

	C1 +	C2 -
ALT1	1.8111111	0.566666667
ALT2	4.822222221	4.82222222
ALT3	4.383333333	3.744444333
ALT4	4.266666667	4.266666667

Table 2. Normalized matrix.

	C1	C2
ALT1	0	1
ALT2	1	0
ALT3	0.854243543	0.253263733
ALT4	0.815498156	0.130548302

Table 3. Final weight.

	STD	Cj	Wj
C1	0.451991552	0.898885218	0.502147102
C2	0.448126262	0.891198235	0.497852898

- For Sub-Criteria of level C1

- The previous steps are also calculated in level C1 the aggregated decision matrix shown in Table 4
- The correlation coefficients for the main criteria and final weights are shown in Table 5.

Table 4. Aggregated matrix.

	C11 +	C12 -	C13 +
A1	5.461111	5.461111	4.383333333
A2	2.55	5.561111	3.527777667
A3	3.744443333	1.811111	1.694444433
A4	3.005555333	3.527777667	2.666666667

Table 5. Final weight.

	STD	Cj	Wj
C11	0.439366356	0.626516576	0.23239672
C12	0.475872169	1.228394786	0.455654216
C13	0.418959407	0.840981145	0.311949064

- For Sub Criteria of level C2

- The previous steps are also calculated in level C2 the aggregated decision matrix shown in Table 6
- The correlation coefficients for the main criteria and final weights are shown in Table 7.

Table 6. Aggregated matrix.

	C21 +	C22 -	C23 +
A1	3.527777667	2.666666667	3.744443333
A2	1.811111	4.483333333	4.383333333
A3	3.527776667	4.722222	6.2
A4	2.666666667	3.744444433	0.616666667

Table 7. Final weight.

	STD	Cj	Wj
C11	0.478854898	0.474602643	0.235711214
C12	0.449534446	0.850828743	0.422563758
C13	0.420652269	0.688060607	0.341725028

Rank alternatives using the SVTrNS-TODIM method for each level

- For the Main Criteria in the First level

- Using the aggregated matrix of level 1 then using Eqs. (12) and (13) to get normalized matrix and Eq. (14) to get relative weight as shown in Table 8.
- The overall dominance degree of each alternative is calculated using Eq. (15) to get the final rank as shown in Table 9.

Table 8. Normalized matrix.

	C1	C2
A1	0.118502363	0.713440104
A2	0.315521628	0.083837437
A3	0.286804798	0.107968691
A4	0.279171211	0.094753769
Wcr	1	0.991448314

‘

Table 9. Final Rank of level1.

Alt	Dominance	RANK
A1	-0.591899692	1
A2	-1.08907829	3
A3	-0.956914075	2
A4	-1.416522855	4
min	-1.416522855	
max	-0.591899692	

- For Sub- Criteria of level C1

- The previous steps are also calculated in level C1 the normalized decision matrix shown in Table 10.
- The overall dominance degree of each alternative and final rank is shown in Table 11.

Table 10. Normalized matrix.

	C11	C12	C13
A1	0.369966156	0.33378608	0.154484174
A2	0.17275124	0.339898135	0.191949633
A3	0.253669502	0.110696091	0.399632833
A4	0.203613102	0.215619693	0.253933361
Wcr	0.510028684	1	0.68461797

Table 11. Final Rank of level C1.

Alt	Dominance	RANK
A1	-1.153428574	1
A2	-2.820205116	3
A3	-1.928458813	2
A4	-3.131941493	4
min	-3.131941493	
max	-1.153428574	

- For Sub Criteria of level C2

- The previous steps are also calculated in level C2 the normalized decision matrix shown in Table 12
- The overall dominance degree of each alternative and final rank is shown in Table 13.

Table 12. Normalized matrix.

	C11	C12	C13
A1	0.305876712	0.348229716	0.250557565
A2	0.157032764	0.207125482	0.293308572
A3	0.305876625	0.196647378	0.414869919
A4	0.2312139	0.247997424	0.040583523
Wcr	0.557812188	1	0.808694597

Table 13. Final Rank of level C2.

Alt	Dominance	RANK
A1	-0.207872866	1
A2	-4.118318128	3
A3	-0.378605571	2
A4	-4.718760856	4
min	-4.718760856	
max	-0.207872866	

5 | Conclusion

The need to combine novel contemporary technologies is inevitable given the rising demands for the quantity and quality of livestock and poultry products. For instance, merging IoTs and their various applications in livestock management became inescapable and unavoidable, particularly in the context of smart cities. The integration of IoT technologies enables farmers to monitor and manage their livestock more efficiently, leading to improved productivity, sustainability, and animal welfare. Based on these insights, the primary contribution of the proposed paper is to develop a systematic and robust method for prioritizing sustainable approaches for smart livestock management in smart cities. Hence, evaluation of the functionality of IoT technologies through their applications based on a set of criteria and sub-criteria is essential.

Moreover, CRITIC-TODIM of MCDM techniques are applied under the authority of the SVTrNS environment to support MCDM techniques in an ambiguous environment. Also, TrST is utilized for forming the determined IoTs' criteria and sub-criteria into Tree form to exhibit the relationship between criteria and sub-criteria. By integrating IoT technologies with advanced decision-making methods, the proposed approach seeks to optimize livestock management practices and contribute to the sustainable development of smart cities. The proposed applications have been subjected to several tests. Decision makers use a hybrid method CRITIC-TODIM method to rank the best application from our experimental Alt 1 as the best IoT application to be used in Livestock management in smart cities. Given the importance of merging contemporary technologies like IoTs as mentioned here, the anticipation of integration of other digital technologies such as Digital Twin, Cobot, and other technologies in livestock management is inescapable in the future scope.

With the continued development of these technologies and the growth of the agri-tech industry, it is expected that farmers will have access to even more advanced and sophisticated tools to manage their livestock. This will result in more sustainable, efficient, and profitable farming practices.

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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.

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