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Recognizing and Prioritizing Smart Solutions in the Poultry Industry based on Sustainability Criteria

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Abstract

Livestock and poultry production and supply is one of the significant food sectors in which more production can lead to a decrease in dependence on exports and earning foreign exchange. Poultry farming is a vital industry for sustainable food supply in all countries. In this research, intelligent applications and solutions in the poultry industry are identified and prioritized using the simultaneous evaluation of criteria and alternatives (SECA) method based on criteria representing the sustainable development. Analysis showed that eighteen principal fields of intelligent solutions are identified in the poultry industry. The weights obtained for sustainable development criteria based on the SECA method are economic (0.351), social (0.3383), and environmental (0.3065) in order of value. Economic sustainability should be most important in implementing smart solutions-based projects in the poultry industry. One of the main challenges of the agricultural sector, especially the poultry industry, is traditional production utilization which leads to the overuse of land capacity. Globalization trends, climate changes, moving from a fossil fuel-based economy to an environment-based economy, competition for land, freshwater, and labor shortage have also led to more complications in supplying nutrition. Considering the potential of smart solutions in realizing sustainable development objectives, it is suggested to focus more on the environmental aspects of poultry industry projects.

Keywords: Internet of things, Poultry industry, Sustainable development, Smart solutions, SECA method

Introduction

Due to its tight relationship with the environment, the agriculture industry has the most destructive effect on the environment (Quintero and González, 2018). In order to realize higher efficiency and greater environmental compliance, we need to identify scientific and environmental-friendly methods. Various variables and parameters are influential in agricultural development, such as water, soil, livestock inputs, organizational services, and proper management of natural resources. One of the challenges of developing countries is the limited resources and ignorance of farmers in correctly using resources (Bani Asadi and Mehrjerdi Zare, 2010). In general, the development of the agricultural sector has various environmental effects, such as the emission of greenhouse gases, the destruction of biodiversity, pollution caused by fertilizers and pesticides, soil degradation, and increased risk to human health (DeLonge, 2016). Considering the importance and role of agriculture in the development of communities and environmental concerns on the one hand and global challenges such as food security and

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population growth on the other hand, it seems necessary to implement extensive measures to realize sustainability in agriculture (Wang, 2017).By achieving targets such as reducing poverty, guaranteeing sustainable patterns of production and consumption, taking immediate action to resolve climate change and its effects, the protectingand sustainable use of oceans, seas, and natural resources (Williams *et al*., 2018), agriculture performs a vital responsibility in achieving the Sustainable Development Goals (SDGs) approved in September 2015 by 193 countries in order to improve the social, economic and environmental conditions of the world (GeSI, 2016).

The Internet of Things (IoT) is one of the innovations of the digital age using advanced and related technologies such as mobile and wireless communication technology, Nano-technology, identification technology based on radio waves, and smart sensor technology that can connect all objects in any time and place by anything or anyone.

One of the applications of IoT is poultry farming, which can turn a manual farm into a modern semi-automatic poultry farm. In addition, the system can be installed on the android mobile applications and help control operations such as feeding, object detection, water spraying, and gas reduction in poultry farms. The proposed system can reduce the need for human labor to feed the chickens, reduce unwanted gas, and control the temperature in the farm fully automatically. Therefore, this system reduces cost, time, workforce, and environmental pollution (Azarinfar, 2015). Another achievement of the IoT is precision livestock farming (PLF) techniques, established in the last few decades.

The world population is expected to reach 10 billion people by 2050 (United Nation Website, 2023). In order to eliminate hunger and supply the necessary food for all these 10 billion people, the current capacity of agriculture should be increased by about 70%. It is impossible to achieve this objective without relying on scientific innovations. Today, smart agriculture, which refers to the usage of technologies like Internet of Things, sensors, location systems, robots and artificial intelligence on farms, has introduced information and communication technologies as an influential factor in the efficiency and profitability of agriculture (O'Grady and O'Hare, 2017).

Information and communication technologies (ICT) have a favorable potential for improving efficiency, effectiveness, and productivity. However, these technologies are rarely used in agriculture. Small changes in production or efficiency can significantly impact the resulting profitability (O'Grady and O'Hare, 2017).Smart agriculture can construct a homogeneous path, including sanctioned techniques and technologies. Such a path is determined through market comparison and segmentation. One of the objectives of smart agriculture is to realize diversity in technologies, network the components of the agricultural sector, and ultimately move crop and livestock production systems toward sustainable agriculture (Walter *et al*., 2017).

Poultry farming is one of the vital industries for sustainable food supply. The implementation of a smart poultry farm (SPF) includes a smart system for automatic food feeding, water sprinklers to control the temperature of the environment, and also the use of soil mixture to reduce gas in the environment. The user can remotely control the system through the android mobile applications. The operation of this smart system, in the first place, leads to the reduction of human labor activity. Also, the development of automatic chicken-feeding devices can be very useful for the growth of the poultry industry. In existing systems, chickens are fed manually by human labor. The proposed system can replace the role of the worker in the nutrition of poultry and fulfill a semi-automatic process in the poultry industry. Also, it is very important to save and adjust the high expenses of poultry houses, including the construction cost, labor cost, fuel costs of heaters, the amount of electricity consumed by lamps and fans and etc. Relying on modern science in the development of SPF provides the possibility of saving costs (Williams *et al*., 2018). Smart systems help poultry farmers to control their poultry farming activities. This system can facilitate poultry management and monitoring with wireless sensors and mobile solutions. Also, environmental parameters such as temperature, light, and ammonia gas are automatically controlled (Archana and Uma, 2018).

The current study regarding the purpose is considered applied research. At the same time, it is classified in the framework of descriptive research because the researcher describes smart solutions in the poultry industry based on sustainability criteria and subsequently evaluates and prioritizes the identified components and criteria in the form of a case study in the poultry industry, especially the laying hens sector. Therefore, considering the potential of the Internet of Things technology and smart solutions in creating a new path of innovative research in the field of agriculture, as well as the increasing speed of the production of scientific resources, it is necessary to identify smart solutions in the poultry industry based on sustainability criteria. To the best of our knowledge, there has been no research on smart solutions in the poultry industry based on sustainability criteria in domestic and foreign literature. As a result, based on the new approach of simultaneous evaluation of criteria and alternatives (SECA) in multi-criteria decision-making, this research has identified smart solutions in the poultry industry and then prioritized these solutions.

Background of Study

Due to the unstable production costs and global economic uncertainty, the role of PLF in sustainable food production and processing is very important. This technique uses wireless technology to collect data through the Internet of Things. One of the goals of smart agricultural systems is providing enough data to producers and ranchers to optimize the efficiency of the agricultural system and, as a result, increase the overall performance of animals or agricultural systems. The major role of PLF is related to the optimal reduction of losses in the entire production process (Molo *et al*., 2009). By reducing the need for manual observations and human decisions, PLF systems facilitate the automation of these processes and reduce the time and effort required to manage large numbers of livestock. PLF systems provide real-time monitoring and livestock management. Livestock management through PLF is sometimes done as a unique livestock management approach (Halachmi *et al*., 2019). This process allows producers to manage a larger number of animals with a reliable level of care (Smith *et al*., 2015). Individual livestock management in large poultry farms containing thousands of birds is not always possible. However, it is possible to use PLF technology to control a subset of birds and use these inputs to assess flock health (Dalimour, 2017). According to previous studies, the review and prioritization of smart solutions in the poultry industry have not been done in any research. After reviewing the research literature, smart applications and sustainability criteria have been identified in the poultry industry, presented in Table1.

Methodology and data

According to the review of the research literature in the field of sustainable development criteria in agriculture, all the final criteria and sub-criteria identified are presented in Table 2. It should be noted that the sustainable development criteria mentioned in agriculture are all in the class of positive criteria.

Methodology Steps

In 2022, about two thousand poultry holdings were active in the laying hens' sector in Iran. The statistical population selected in this research includes faculty members of Alzahra university and poultry industry experts on poultry industry management and smart computer applications. The statistical sample of this research is selected from among the companies active in the poultry industry based on sampling methods.

Table 1- Identifying innovative smart applications in the poultry industry

Application	Resource	Field
Environmental monitoring systems (To control environmental inputs, including temperature, air speed, ventilation rate, substrate quality, humidity and concentration of gases such as carbon dioxide and ammonia)	(Chowdhury and Morey, 2019), (Bora *et al*., 2020), (Bustamante *et al*., 2012), (David *et al*.,2015), (Jackman *et al*., 2015), (Calvet *et al*., 2014), (Epp, 2019), (Bordin *et al*.,2013), (McDougal,2018)	IoT
Precision feeding systems (Technology to achieve accurate food conversion rate and maintain bird weight)	(Astill *et al*., 2020),(Park *et al*., 2022), (Zuidhof *et al*., 2017), (Hadinia *et al*., 2018), (Zuidhof, 2018), (Xin and Liu, 2017)	
Poultry welfare monitoring systems (Technology to understand the welfare of birds in terms of temperature, humidity, etc.)	(Melor *et al*., 2020), (Astill *et al*., 2020),(Park *et al*., 2022),(Sassi *et al*., 2016)	
Digital imaging (Achieving movement patterns of chickens to evaluate factors related to welfare)	(Corkery *et al*., 2013), (Marchoka *et al*., 2013), (Silvera *et al*., 2017), (Colles *et al*., 2016), (Sassi *et al*., 2016), (Vanderhasselt *et al*., 2013)	
Analysis of bird sounds (Evaluation of the sound of birds as an indicator of health and welfare)	(Manteuffel *et al*., 2004), (Fontana *et al*., 2015), (Bright, 2008), (Carroll *et al*., 2014), (Rizwan *et al*., 2017)	
Infrared thermal imaging (Control of the chicken's health status by determining the surface temperature of objects based on infrared rays)	(Nääs *et al*., 2014), (Shinder *et al*., 2019)	
Raman spectroscopy (Imaging technique to assess the gender of the chicken embryo)	(Galli *et al*., 2016), (Neethirajan *et al*., 2017), (Carol *et al*., 2014), (Galli *et al*., 2016), (Peebles,2018)	
Wearable sensors for the detection of avian influenza virus (Clinical symptom detection sensor and quick virus diagnosis)	(Neethirajan*et al*., 2017), (Okada *et al*., 2009), (Okada *et al*., 2014)	
Avian influenza virus biosensors (Biological receptor to detect the presence of a pathogen, protein, nucleic acid, etc.)	(Astill *et al*. 2020), (Nuñez and Ross, 2019), (Luka *et al*., 2015), (Chen and Neethirajan, 2015)	
Internet of things and smart poultry farming	(Park *et al*., 2022), (Banhazi, 2009),(Bello and Zeadally,2015),(Zuidhof *et al*., 2017)	
Clustering to monitor the growth status of chickens and real-time disease diagnosis	(Aengwanich *et al*., 2012), (Ghufran Ahmed *et al*., 2021)	Data mining
PLF technology and data	(Astill *et al*., 2020), (Banhazi, 2009)	
Data collection and storage	(Banhazi, 2009), (Schuetz *et al*., 2018), (Smith *et al*., 2015), (Chen *et al*., 2014), (Wolfert *et al*., 2017)	
Data access for smart poultry management systems	(Bumanis *et al*., 2022), (Davis, 2016)	
Data governance	(Information Builders, 2011), (Wizman *et al*., 2018), (Saykota, 2016)	
Big data analysis systems in the poultry industry	(Sicular, 2013), (Kamilaris *et al*., 2017), (Wolffort *et al*., 2017), (Chen *et al*., 2014), (Manika *et al*., 2011)	
Tracking the chickens in poultry halls to determine the time of rest, the time of feeding, etc.	Ronald and Siarhei, 2012), (Rani and Devarajan, 2012), (Praveen and Satish, 2012), (Zhang *et al*., 2007)	RFID Tags
Mobile management system and farm management system to transfer and receive farm environmental information	Chakchai *et al*., 2014	Mobile technology and GPS mapping

Note: a. abbreviation: Radio-frequency identification (RFID)

Table 2- The final criteria of sustainable development

The main criterion	Sub criterion	Resource
Economical	Productivity	(Veisi *et al*., 2016; Chiou *et al*., 2005; Quaddus and Siddique, 2001; Rezaei Moghaddam and Karami, 2008)
	Profitability	(Rezaei-Moghaddam and Karami, 2008; Quaddus and Siddique, 2001)
	Employment	(Senoret *et al*., 2022), (Rezaei-Moghaddam and Karami, 2008)
Social	Quality of life	(Comim and Hirai, 2022), (Rezaei-Moghaddam and Karami, 2008)
	Fairness	(Quaddus and Siddique, 2001; Rezaei-Moghaddam and Karami, 2008)
	Partnership	(Rezaei-MoghaddamandKarami,2008)
Environmental	Environmental protection	(Gunnarsdottir *et al*., 2022), (Comim and Hirai, 2022), (Rezaei-Moghaddam and Karami, 2008); (Zarei, Mohammadian and Ghasemi, 2016)
	Reasonable use of resources	(Rezaei-MoghaddamandKarami, 2008)
	Quality of products	(Bordin *et al*., 2022), (Rezaei-Moghaddam and Karami, 2008; Poursaeed *et al*., 2010)

A total of 40 questionnaires have been distributed among 20 experts. The first 20 questionnaires have been distributed to identify the components and change and remove some components. The information from the second batch of questionnaires has been used to prioritize alternatives and criteria through the SECA method. This method was presented by Keshavarz-Ghorabaee *et al.* (2018) in research entitled "simultaneous evaluation of criteria and alternatives in multi-criteria decision making."The purpose of this method is to determine the total score of the alternatives and the weight of the criteria at the same time. To achieve this goal, a multi-objective nonlinear mathematical model is formulated.

Research Steps

In order to identify and prioritize smart solutions in the poultry industry based on sustainability criteria, a literature review and a study of references and background papers have been studied. As Figure 1 illustrates the steps of methodology including i) extracting criteria from literature review and interviewing with exert; ii) the relevant components and indicators were identified and finalized through consultation with experts; iii) subsequently, the importance score and weight of the criteria have been calculated with the help of poultry industry experts through the SECA method and Finally, iv) their prioritization and evaluation have been completed (Keshavarz-Ghorabaee *et al.*, 2018).

SECA Method

The steps to implement the SECA method proposed by Keshavarz-Ghorabaee *et al.* (2018) are as follows:

First, the n× m decision matrix, including n alternatives and m criteria, is prepared as follows.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix}$$

Where X_{ij} is the evaluation of the i^{th} alternative concerning the j^{th} criterion.

Then the decision matrix is normalized based on the following relations:

$$X^N = \begin{bmatrix} x_{11}^N & \cdots & x_{1m}^N \\ \vdots & \ddots & \vdots \\ x_{n1}^N & \cdots & x_{nm}^N \end{bmatrix}$$

$$x_{ij}^N = \begin{cases} \dfrac{x_{ij}}{\max k\, x_{kj}} & if\ j \in BC \\ \dfrac{\min\ k\, x_{kj}}{x_{ij}} & if\ j \in NC \end{cases}$$

Where BC includes profit-focused criteria (or positive criteria), and NC includes cost-focused criteria (or negative criteria).

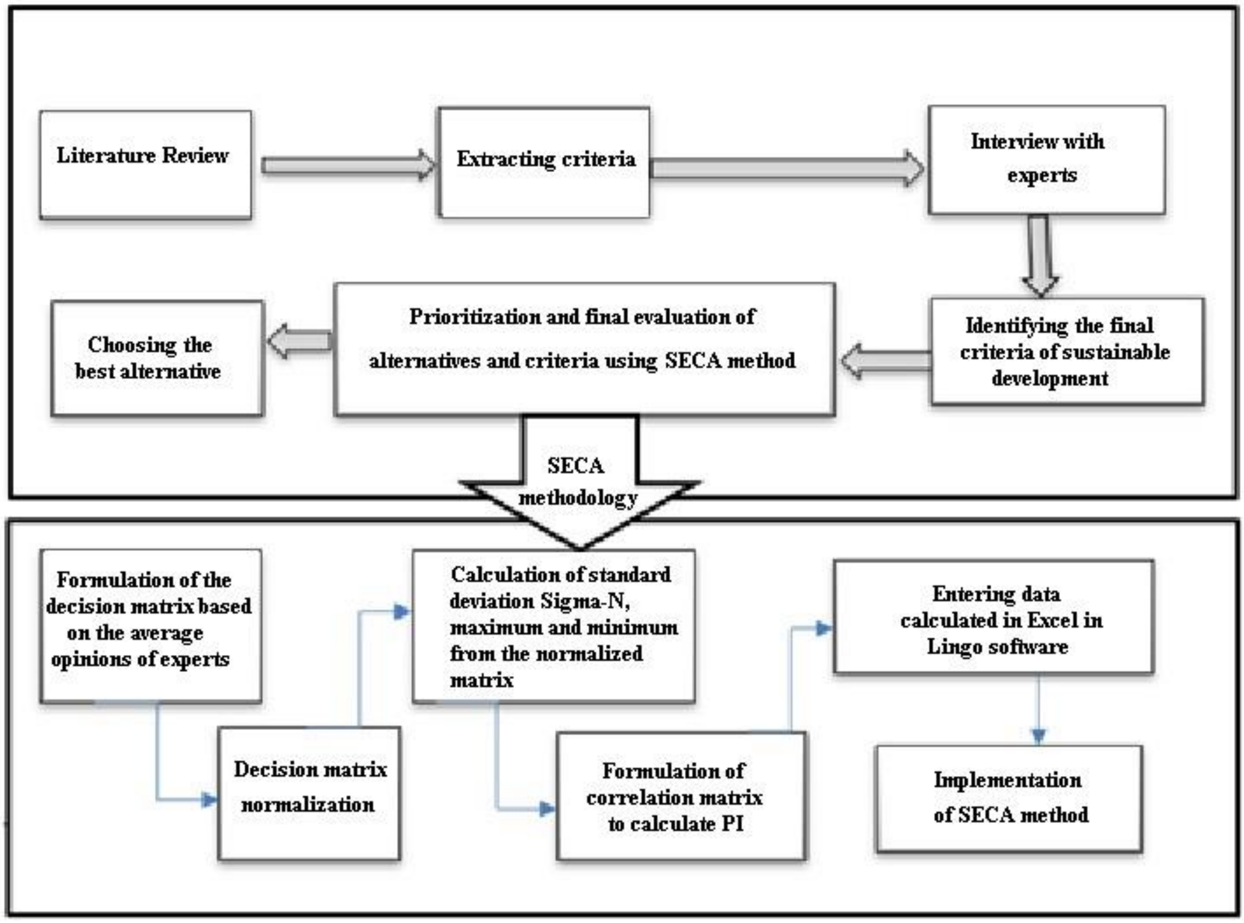

Figure 1- The research procedure

The standard deviation of the elements of each vector can provide the information of intra-criteria. The correlation between each pair of criteria vectors in the decision matrix is calculated to obtain information on inter-criteria. This correlation is denoted by rji. The following relationship can show the difference between the jth criterion and other criteria.

$$\pi j = \sum_{i=1}^{m} (1 - rji) \quad (1)$$

Increasing the variance in the vector of a criterion (j) and increasing the difference between criterion j and other criteria increases the importance (weight) of the criterion. Accordingly, the normalized values of σ_j^N and π_j^N are defined as reference points for the weights of the criteria. These values can be calculated as follows:

$$\sigma_j^N = \frac{\sigma_j}{\sum_{i=1}^{m} \sigma_i} \quad (2)$$

$$\pi_j^N = \frac{\pi_j}{\sum_{i=1}^{m} \pi_i} \quad (3)$$

In light of the above, a nonlinear multi-objective programming model is obtained as follows:

$$max\, S_i = \sum_{j=1}^{m} w_j x_{ij}^N \quad , \quad \forall_i \in \{1,2,3,\cdots,n\} \quad (4)$$

$$min\, \lambda_b = \sum_{j=1}^{m} (w_j - \sigma_j^N)^2 \quad (5)$$

$$min\, \lambda_c = \sum_{j=1}^{m} (w_j - \Pi_j^N)^2 \quad (6)$$

$$\text{s.t} \sum_{j=1}^{m} w_j = 1 \quad (7)$$

$$w_j \leq 1,\ \forall_i \in \{1.2.3 \cdots m\} \quad (8)$$

$$w_j \geq,\ \forall_i \in \{1.2.3 \cdots m\} \quad (9)$$

Equation 4 increases the overall performance of each alternative. Also, equations 5 and 6 minimize the weight criteria deviation from each criterion's reference points. Equation 7 guarantees that the sum of the weights is equal to 1. Equations 8 and 9 determine the weights of the criteria for some values in the interval $[\varepsilon, 1]$. It should be said that ε is a small positive parameter considered a lower bound for the criterion weight. In this method, the value of this parameter is set equal to 0.003. To optimize the above model, we can convert the objective function into a constraint. A single-objective relationship is formulated as follows.

$$Max\ Z = \lambda_a - \beta(\lambda_b + \lambda_c) \quad (10)$$

$$\text{s.t}\ \lambda_a \leq S_i\ ,\ \forall_i \in \{1,2,3,\cdots,n\} \quad (11)$$

$$S_i = \sum_{j=1}^{m} w_j\, x_{ij}^N = 1 \quad , \quad \forall_i \in \{1.2.3\ \cdots n\} \quad (12)$$

$$\lambda_a = \sum_{j=1}^{m} (w_j - \sigma_j^N)^2 \quad (13)$$

$$\lambda_a = \sum_{j=1}^{m} (w_j - \Pi_j^N)^2 \quad (14)$$

$$\sum_{j=1}^{m} w_j = 1 \quad (15)$$

$$w_j \leq 1, \forall_i \in \{1,2,3,\cdots,m\} \quad (16)$$

$$w_j \geq\ , \forall_i \in \{1,2,3,\cdots,m\} \quad (17)$$

According to the objective function of the model above, the minimum overall performance score of the alternatives is maximized. Since the deviation from the reference points must be minimal, their differences from the objective function are calculated with the coefficient B. This coefficient affects the importance of achieving reference points of weight criteria. The overall performance score of each alternative (Si) and the weight of each criterion (wj) are determined by solving this model. Model formulation and calculations have been done in Lingo software.

Data Acquisition

Primary data, including smart solutions and sustainable development criteria in the poultry industry, have been extracted and listed in the Table 3.

Using the questionnaire, extracting options related to smart solutions in the poultry industry will be prioritized based on sustainable development criteria in agriculture.

Results

The proposed model can simultaneously determine the overall performance score of the alternatives and the objective weight of the poultry industry's criteria. In order to verify the SECA method, the objective weight of the criteria and the overall performance of the resulting alternatives are analyzed.

Table 3- Related alternatives to smart solutions in the poultry industry

Alternatives	Symbol
Environmental monitoring systems	A1
Precision feeding systems	A2
Welfare monitoring systems	A3
Digital imaging	A4
Analysis of bird sounds	A5
Infrared thermal imaging	A6
Raman spectroscopy	A7
Wearable sensors for the detection of avian influenza virus	A8
Avian influenza virus biosensors	A9
Internet of things and smart poultry farming	A10
Clustering to monitor the growth status of chickens and real-time disease diagnosis	A11
PLF technology and data	A12
Data collection and storage	A13
Data access for smart poultry management systems	A14
Data governance	A15
Big data analysis systems in the poultry industry	A16
Tracking the chickens in poultry halls Using RFID tags	A17
Mobile management system and GPS mapping	A18

Table 4- Related alternatives to smart solutions in the poultry industry

Attributes	Symbol
Productivity	C1
Profitability	C2
Employment	C3
Quality of Life	C4
Fairness	C5
Partnership	C6
Environmental protection	C7
Reasonable use of resources	C8
Quality of products	C9

The results show that determining the appropriate value for the component (β) facilitates the determination of the sustainability weight for the criteria and performance scores of the alternatives. Finally, the results of the SECA method are compared with the results of the SD and CRITIC methods.

Related alternatives to smart solutions in the poultry industry are listed in Table 4.

In this section, final model is executed using the normalized decision matrix table data and various values for the coefficient β = (0.1, 0.2, 0.3, 0.4, 0.5, 1, 2, 3, 4, 5). After execution of the model, ten sets of weights for the criterion are obtained. The different weight values of the criteria resulting from the change of β value are shown in Table 3. Figure 2 also shows the variation of these weights.

Table 3- Different weight values of the criteria resulting from changing the value of β

	β									
	0.1	0.2	0.3	0.4	0.5	1	2	3	4	5
W1	0.1273	0.1550	0.1571	0.1539	0.1517	0.1404	0.1339	0.1278	0.1247	0.1228
W2	0.1281	0.1197	0.1208	0.1217	0.1225	0.1162	0.1097	0.1083	0.1077	0.1072
W3	0.2751	0.2368	0.2001	0.1789	0.1661	0.1375	0.1271	0.1200	0.1164	0.1142
W4	0.2743	0.2579	0.2158	0.2025	0.1952	0.1617	0.1311	0.1230	0.1191	0.1166
W5	0.0246	0.0783	0.0939	0.1123	0.1240	0.1283	0.1215	0.1159	0.1131	0.1113
W6	0.0010	0.0010	0.0010	0.0010	0.0010	0.0498	0.0880	0.0994	0.1049	0.1085
W7	0.1457	0.1188	0.1281	0.1326	0.1351	0.1325	0.1284	0.1259	0.1245	0.1238
W8	0.0010	0.0010	0.0362	0.0479	0.0542	0.0770	0.0963	0.1019	0.1046	0.1064
W9	0.0230	0.0316	0.0469	0.0492	0.0501	0.0565	0.0640	0.0778	0.0850	0.0892

Table 4- Ranking criteria according to different values of β

rank	*β*									
	0.1	0.2	0.3	0.4	0.5	1	2	3	4	5
W1	5	3	3	3	3	2	1	1	1	2
W2	4	4	5	5	6	6	6	6	6	7
W3	1	2	2	2	2	3	4	4	4	4
W4	2	1	1	1	1	1	2	3	3	3
W5	6	6	6	6	5	5	5	5	5	5
W6	8	8	9	9	9	9	8	8	7	6
W7	3	5	4	4	4	4	3	2	2	1
W8	8	8	8	8	7	7	7	7	8	8
W9	7	7	7	7	8	8	9	9	9	9

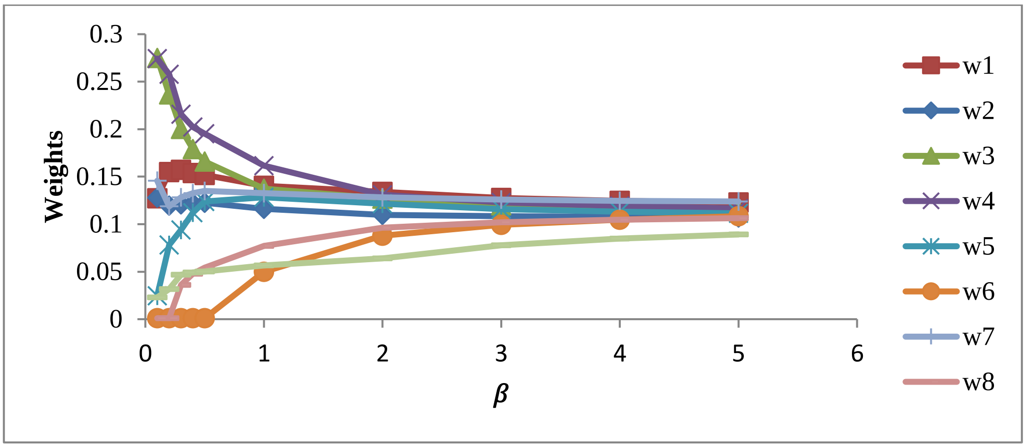

Figure 2- Variation of criteria weight according to different values of β

As shown in Figure 2, when the values of β are greater than 3 (β ≥ 3), the criteria weights are more sustainable.

Now, to verify the results, the criteria weights are also determined using other methods. Two methods, SD and CRITIC, have been chosen for comparative analysis. The weights of the criteria obtained from these three methods are shown in Table 5. If the correlation value is greater than 0.6, there is a reasonable link between the results (Walters, 2009). Table 6 shows the correlation values between the results.

Table 5- Comparing the objective weight of criteria with other methods

	STD	CRITIC
W1	0.1022	0.1155
W2	0.1082	0.1104
W3	0.1020	0.1178
W4	0.1084	0.1073
W5	0.0883	0.1295
W6	0.1259	0.1187
W7	0.1122	0.1121
W8	0.1264	0.1041
W9	0.1266	0.0845

Table 6- Correlation between the weights of the criteria according to the values of β

	STD	CRITIC
0.1	-0.4168	0.1174
0.2	-0.5770	0.2065
0.3	-0.6275	0.2046
0.4	-0.6889	0.2410
0.5	-0.7273	0.2676
1	-0.7805	0.4223
2	-0.7594	0.6431
3	0.6903	0.6596
4	0.6145	0.6567
5	0.5272	0.6477

As shown in Table 6, the correlation values for β ≥ 3 are greater than 0.6 (these values are highlighted in bold in the table). Likewise, β=3 can be a suitable threshold value for performing calculations in the proposed method.

Now, the overall performance score of each criterion is calculated by the proposed model based on the normalized decision matrix table, as well as β values and, subsequently, the weight of the obtained criteria. The calculated scores of the alternatives' overall performance and correlation ranking are presented in Tables 7 and 8, respectively. Additionally, performance scores are visualized in Figure 3.

Table 7- Overall performance scores of alternatives with different values of β

	β									
	0.1	0.2	0.3	0.4	0.5	1	2	3	4	5
S1	0.683	0.671	0.652	0.647	0.644	0.627	0.612	0.603	0.598	0.596
S2	0.653	0.650	0.628	0.618	0.612	0.578	0.553	0.539	0.532	0.528
S3	0.636	0.629	0.615	0.610	0.606	0.582	0.564	0.553	0.548	0.545
S4	0.709	0.716	0.690	0.681	0.677	0.639	0.609	0.592	0.584	0.579
S5	0.734	0.753	0.727	0.724	0.723	0.681	0.641	0.624	0.615	0.609
S6	0.657	0.674	0.656	0.651	0.649	0.615	0.586	0.570	0.563	0.558
S7	0.674	0.678	0.656	0.649	0.645	0.614	0.589	0.576	0.569	0.565
S8	0.796	0.784	0.752	0.740	0.733	0.689	0.656	0.639	0.631	0.626
S9	0.722	0.722	0.695	0.686	0.682	0.642	0.610	0.594	0.586	0.581
S10	0.652	0.650	0.631	0.627	0.625	0.595	0.569	0.557	0.551	0.547
S11	0.672	0.680	0.667	0.661	0.657	0.630	0.610	0.598	0.592	0.588
S12	0.750	0.758	0.727	0.718	0.714	0.674	0.640	0.623	0.615	0.609
S13	0.636	0.639	0.622	0.617	0.615	0.583	0.556	0.543	0.536	0.532
S14	0.642	0.640	0.616	0.610	0.606	0.575	0.550	0.536	0.530	0.526
S15	0.672	0.673	0.671	0.671	0.671	0.650	0.634	0.625	0.621	0.618
S16	0.636	0.629	0.615	0.610	0.606	0.575	0.550	0.548	0.548	0.548
S17	0.636	0.629	0.615	0.610	0.606	0.575	0.550	0.536	0.530	0.526
S18	0.636	0.629	0.615	0.610	0.606	0.616	0.626	0.624	0.622	0.621

Table 8- Ranking the overall performance scores of alternatives according to different values of β

	β									
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**1**	**2**	**3**	**4**	**5**
A1	6	10	10	10	10	8	6	6	6	6
A2	11	11	12	12	13	15	15	16	16	16
A3	14	15	17	17	14	14	13	13	14	14
A4	5	5	5	5	5	6	9	9	9	9
A5	3	3	3	2	2	2	2	3	4	4
A6	10	8	8	8	8	10	11	11	11	11
A7	7	7	9	9	9	11	10	10	10	10
A8	1	1	1	1	1	1	1	1	1	1
A9	4	4	4	4	4	5	7	8	8	8
A10	12	12	11	11	11	12	12	12	12	13
A11	9	6	7	7	7	7	8	7	7	7
A12	2	2	2	3	3	3	3	5	5	5
A13	14	14	13	13	12	13	14	15	15	15
A14	13	13	14	14	14	18	16	17	17	17
A15	8	9	6	6	6	4	4	2	3	3
A16	16	15	15	14	14	16	16	14	13	12
A17	16	15	17	14	14	16	16	17	17	18
A18	16	15	15	17	14	9	5	4	2	2

Table 9- Spearman's correlation coefficient of the resulting ranks

	β									
	0.1	0.2	0.3	0.4	0.5	1	2	3	4	5
0.1	1.000	0.964	0.947	0.938	0.938	0.843	0.759	0.672	0.619	0.613
0.2	0.964	1.000	0.977	0.969	0.963	0.836	0.722	0.640	0.596	0.590
0.3	0.947	0.977	1.000	0.986	0.986	0.894	0.782	0.720	0.679	0.673
0.4	0.938	0.969	0.986	1.000	0.990	0.870	0.735	0.673	0.622	0.614
0.5	0.938	0.963	0.986	0.990	1.000	0.915	0.793	0.729	0.679	0.668
1	0.843	0.836	0.894	0.870	0.915	1.000	0.959	0.926	0.896	0.885
2	0.759	0.722	0.782	0.735	0.793	0.959	1.000	0.976	0.959	0.948
3	0.672	0.640	0.720	0.673	0.729	0.926	0.976	1.000	0.992	0.987
4	0.619	0.596	0.679	0.622	0.679	0.896	0.959	0.992	1.000	0.997
5	0.613	0.590	0.673	0.614	0.668	0.885	0.948	0.987	0.997	1.000

As shown in Figure 3 and Table 7, when the value of β is greater than 3 (β ≥3), the performance of alternatives is more distinct and stable.

In order to check the sustainability of the ranking criteria in different values of β, the Spearman correlation coefficient of the rankings in each column of Table 8 is calculated. The results are reflected in Table 9. As shown in Table 9, when the values of β are greater than 1, the ranks have complete sustainability. It can be said that β=3 is a suitable threshold value for determining the overall performance score and ranking of alternatives.

The results show that determining the appropriate value for the coefficient (β) facilitates realizing the sustainability weight for the criteria and performance scores for the alternatives. Table 10 shows the weight of sustainability criteria for β =3.

Table 11 shows the prioritization of alternatives based on the resulting performance scores.

Smart solutions in the poultry industry in order of priority are rapid diagnosis/point of care diagnosis, smart systems for poultry management, analysis of bird sounds, mobile technology, GPS mapping, sensors, and new technologies in poultry operations, environmental monitoring systems, communication between sensors and used equipment, wearable sensors to detect avian influenza viruses, digital imaging, Raman spectroscopy, infrared thermal imaging, biosensors for detection of avian influenza virus, welfare monitoring systems, data privacy and security, distributed data storage systems, precision feeding systems, poultry tracking using RFID tags, and other data storage systems such as cloud-based operating systems and hybrid storage systems (Table 11).

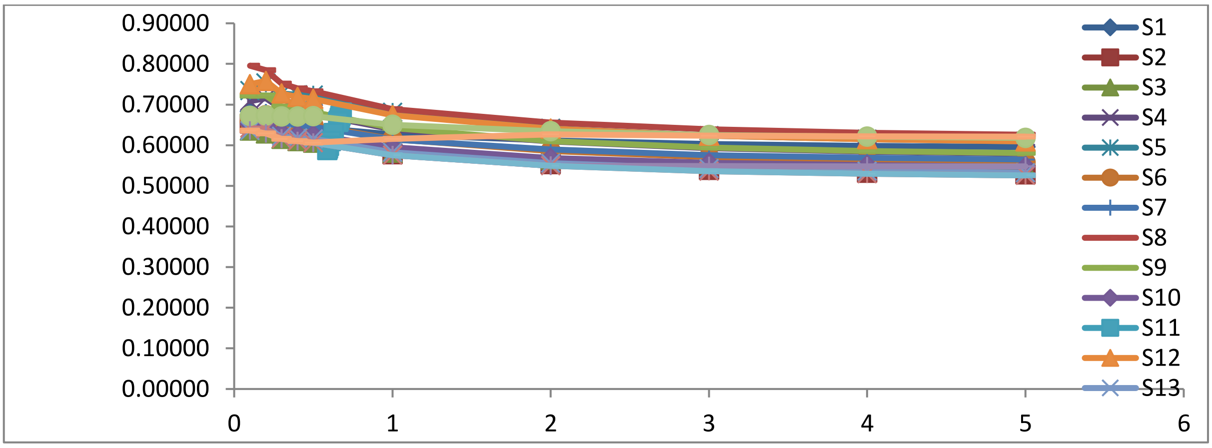

Figure 3- Variability in overall performance scores associated with β value

Table 10- Prioritizing sustainability criteria in the poultry industry based on the SECA method for (β =3)

Criteria symbol	Criteria	Weight of criteria	Ranking of criteria
C1	Productivity	0.1278	1
C 2	Profitability	0.1083	6
C 3	Employment	0.1200	4
C 4	Quality of Life	0.1230	3
C 5	Fairness	0.1159	5
C 6	Partnership	0.0994	8
C 7	Environmental protection	0.1259	2
C 8	Reasonable use of resources	0.1019	7
C 9	Quality of products	0.0778	9

Table 11- Prioritizing solutions and achievements based on smart applications in the poultry industry based on the SECA method according to (β=3)			
Alternatives symbol	Alternatives	Weight of alternatives	Ranking
A1	Environmental monitoring systems	0.603	6
A2	Precision feeding systems	0.539	16
A3	Poultry welfare monitoring systems	0.553	13
A4	Digital imaging	0.592	9
A5	Analysis of bird sounds	0.624	3
A6	Infrared thermal imaging	0.570	11
A7	Raman spectroscopy	0.576	10
A8	Rapid diagnosis/point of care diagnosis	0.639	1
A9	Wearable sensors for the detection of avian influenza virus	0.594	8
A10	Avian influenza virus biosensors	0.557	12
A11	Communication between sensors and equipment used	0.598	7
A12	Sensors and new technologies in poultry operations	0.623	5
A13	Distributed data storage systems	0.543	15
A14	Other data storage systems, such as cloud-based operating systems and hybrid storage systems	0.536	17
A15	Smart systems for poultry management	0.625	2
A16	Data privacy and security	0.548	14
A17	Poultry tracking using RFID tags	0.536	17
A18	Mobile technology and GPS mapping	0.624	4

Conclusion

Over the past few decades, various methods for multi-criteria decision-making have been proposed. Most of these methods evaluate several alternatives based on a default set of criteria weights. In addition, there are methods to determine the objective and subjective weight of the criteria. In this study, a new approach was introduced for applying the method of simultaneous evaluation of criteria and alternatives (SECA). Subsequently, a nonlinear multi-objective mathematical model was formulated based on the introduced approach. The objective function of the model seeks to maximize the overall performance of each alternative according to the diversity of intra-criteria and inter-criteria information and the decision matrix. The results show that determining the appropriate value for the coefficient (β) can facilitate the determination of sustainability weights for criteria and performance scores for alternatives. In the research process, smart solutions in the poultry industry were first identified based on the SECA method. Based on the analysis, 18 main areas of smart solutions in the poultry industry were determined. The identified innovative applications were prioritized based on sustainable development criteria in the next step.

The weights obtained for sustainable development criteria based on the SECA method are economic (0.351), social (0.3383), and environmental (0.3065) in order of value. Economic sustainability should be most important in implementing smart solutions-based projects in the poultry industry. One of the main challenges of the agricultural sector, especially the poultry industry, is traditional production utilization which leads to the overuse of land capacity. Also, the globalization trends, climate changes, moving from a fossil fuel-based economy to an environment-based economy, competition for land, freshwater, and labor shortage have led to more complications in supplying nutrition. Considering the potential of smart solutions in realizing sustainable development objectives, it is suggested to focus more on the environmental aspects of poultry industry projects.

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شناسایی و اولویت‌بندی راه‌حل‌های هوشمند در صنعت طیور براساس معیارهای پایداری

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چکیده

یکی از بخش‌های غذایی که تولید هر چه بیشتر در آن می‌تواند ضمن از بین بردن وابستگی به خارج صادرات ارزآوری نیز داشته باشد، بخش تولید و عرضه دام و طیور است. مرغداری صنعت مهمی برای تأمین پایدار غذا در کشورها می‌باشد. در این پژوهش کاربردها و راه‌حل‌های هوشمند در صنعت طیور شناسایی شده و با استفاده از شاخص‌های توسعه پایدار و با بهره‌گیری از روش ارزیابی همزمان معیارها و گزینه‌ها (SECA) به اولویت‌بندی این کاربردها پرداخته شده است. بر اساس تحلیل‌های صورت گرفته ۱۸ حوزه اصلی از راه‌حل‌های هوشمند در صنعت مرغداری شناسایی گردیده است. اوزان شاخص‌های توسعه پایدار بر اساس روش SECA، اقتصادی (۰/۳۵۱)، اجتماعی (۰/۳۳۸۳) و زیست محیطی (۰/۳۰۶۵) نشان می‌دهد که برای پیاده سازی پروژه‌های مبتنی بر راه‌حل‌های هوشمند در صنعت مرغداری بایستی بیشتر به پایداری اقتصادی اهمیت داد. این در حالیست که یکی از چالش‌های اصلی که بخش کشاورزی بخصوص صنعت مرغداری با آن روبرو است استفاده از روش‌های تولید کشاورزی سنتی است که باعث شده بیش از ظرفیت زمین استفاده کند. علاوه بر آن جهانی شدن، تغییرات آب و هوایی، حرکت از اقتصاد مبتنی بر سوخت فسیلی به سوی اقتصاد مبتنی بر محیط‌زیست و رقابت بر سر زمین، آب شیرین و نیروی کار منجر به پیچیدگی‌های بیشتر و ایجاد چالش تغذیه در جهان و بهره‌برداری اضافی شده است. با توجه به پتانسیل بالقوهٔ راه‌حل‌های هوشمند در تحقق اهداف توسعهٔ پایدار، پیشنهاد می‌شود که بیشتر بر روی جنبه زیست‌محیطی پروژه‌ها تمرکز شود.

واژه‌های کلیدی: اینترنت اشیا، توسعهٔ پایدار، راه‌حل‌های هوشمند، روش SECA، صنعت طیور

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