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Intelligent Expert Systems Using Molecular Fuzzy Genetic Algorithms and Multi-Objective Particle Swarm Optimization for Circular-Oriented Project Investments

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Abstract. Circular-oriented project investments promote sustainable growth by enhancing resource efficiency and minimizing waste. There is a significant gap in the literature to identify key variables that influence the performance of these investments. This gap can cause inappropriate decisions by investors and policymakers, as well as inefficient resource utilization by businesses. To address this missing gap, this study aims to identify the key indicators influencing circular-oriented project investments by introducing a novel decision-making model. The proposed model integrates the information gain technique for project prioritization, Q-learning for expert evaluation, genetic algorithms for criteria weighting, and swarm optimization for alternative ranking. The main contribution of this study is that molecular fuzzy sets are considered by combining molecular geometry and fuzzy logic. These sets offer a more advanced uncertainty modeling capability than traditional fuzzy sets. The application of genetic algorithms in criteria weighting provides a significant contribution to the literature. By making a global optimization, more appropriate calculations can be performed for criteria weighting. The findings denote that emission reduction and financial performance are the most crucial criteria for the performance improvements of these projects. Moreover, waste-to-energy plants and urban mining initiatives are found as the most significant project alternatives.

Key-words: Circular-oriented projects; genetic algorithms; molecular fuzzy sets; swarm optimization.

1. Introduction

Circular-oriented project investments refer to projects that encourage sustainable growth [1]. These projects aim to use resources more efficiently and reduce waste. Therefore, it is possible to talk about some advantages of these projects [2]. These investments increase economic sustainability by reducing dependency on raw materials [3]. On the other hand, they enable the development of new production processes and business models [4]. Owing to these advantages, some factors for the development of these projects need to be improved. As a result of the literature review, it is seen that some variables play a very critical role in the performance of these projects [5]. Financial performance is an important variable to increase the effectiveness of circular-oriented project investments. Circular economy-oriented projects have high initial costs. Strong financial performance shortens the payback period of the investment [6]. This makes the projects more attractive. Effective waste management can be taken into consideration to achieve this goal. Circular projects reduce the need for raw materials by focusing on recyclable and reusable materials [7]. On the other hand, low-carbon production processes make it easier to comply with legal regulations that will tighten in the future [8]. This also offers the advantage of avoiding penalties [9]. Similarly, circular efficiency minimizes costs in production processes by reducing raw material consumption [10]. This situation contributes significantly to increasing the financial performance of the projects [11].

There are few studies on determining the variables that affect the performance of circular-oriented project investments [12]. This is an important deficiency in the literature. This deficiency may cause investors and policy makers to make wrong or incomplete decisions [13]. On the other hand, this situation may also cause businesses to use their resources inefficiently. To eliminate this deficiency, priority analyses should be carried out in which the importance weights of these criteria are determined [14]. The weights of the variables should be determined using multi-criteria decision-making techniques, artificial intelligence and optimization algorithms [15]. The important issue in this process is the necessity of choosing the right fuzzy numbers and techniques [16]. Otherwise, it will not be possible to manage the uncertainty in the analysis process correctly. To address this missing gap in the literature, this study aims to identify key indicators of circular-oriented project investments. To achieve this objective, a novel decision-making model is established by integrating information gain technique for project prioritization, Q-learning for expert evaluation, genetic algorithm for criteria weighting and swarm optimization for alternative ranking. The main contribution of this model is detailed as follows. (1) Molecular fuzzy sets are also considered to minimize the uncertainty by combining molecular geometry and fuzzy logic. These sets offer a more advanced uncertainty modeling capability than classical fuzzy sets. Classical fuzzy sets are usually based on fixed membership functions. However, molecular fuzzy sets can dynamically update the relationships between variables. In addition, these numbers increase the performance of optimization algorithms by utilizing molecular structure analysis. (2) The use of genetic algorithms in criterion weighting provides significant contributions to the literature. This approach is an optimization method inspired by biological evolution processes. Owing to this issue, a powerful alternative is presented to determine criterion weights in complex decision problems. This technique can provide advantages over classical methods in areas where uncertainty is intense, such as energy investments. Techniques such as criteria importance through intercriteria correlation (CRITIC) and analytical hierarchy process (AHP) perform data-based criterion weighting. On the other hand, genetic algorithms can perform global optimization.

The manuscript is organized with four different sections. Proposed model is explained in the following section. Analysis results are given in the next part. The main concluding remarks are shown in the fourth section.

2. Proposed Methodology

This paper, which determines suitable circular-oriented project investments, proposes an intelligent expert system using molecular fuzzy genetic algorithms and multi-objective particle swarm optimization. In this system, while the information gain-based attribute selection algorithm is taken as reference to reduce the number of project alternatives, the Q-learning algorithm is used to transform the opinion matrices of decision makers (DMs) into balanced structures. After the construction of balanced opinion matrices, decision criteria are first prioritized using genetic algorithms and then the reduced project alternatives are ranked with swarm optimizations. In this process, uncertainty is included in the analysis with the help of molecular fuzzy sets. The operation of the system is visualized in Figure 1.

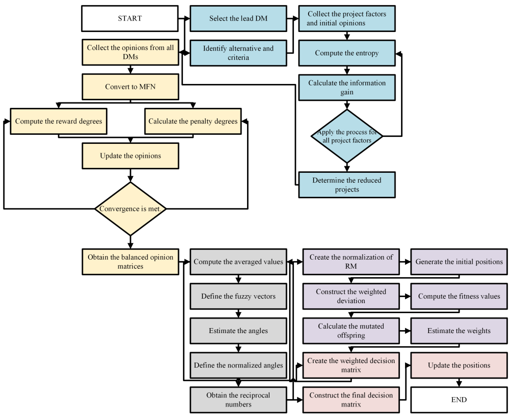

Fig. 1. Proposed Model.

2.1. Information Gain-Based Project Prioritization

The characteristics of the projects and the Likert ratings of the DMs are collected. Based on the opinions of the DMs, the DM choices of each outcome are measured by measuring the uncertainty or distortion in the ratings of each criterion among the projects using the entropy measure of each outcome [17]. This measure is calculated by Entropy:

$$Entropy(cr) = -\sum_{i=1}^{n} pr_i \log_2 pr_i \tag{1}$$

In this equation, cr means the criteria in the output and n refers the level of the unique rating. pr is the probability of ratings in the project dataset. Later, the information gain values are obtained for inputs attributes determining the project specification in terms of.

$$IG_{Att,cr} = Entropy(cr) - \sum_{v \in ATT} \frac{|cr_v|}{|cr|} Entropy(cr_v) \tag{2}$$

Where $|cr|$ and $|cr_v|$ are the sizes of the dataset and subset. In another step, the weighted entropies for outputs are computed by the weights of the project input in the total projects. Then, the overall entropies are defined. Similarly, the calculation is performed for all project attributes. Finally, the most suitable project input is determined according to the maximum of the information gain.

2.2. Q-learning

Criteria and alternatives are defined. DMs express their opinions on these concepts. These opinions are converted into molecular fuzzy numbers and thus fuzzy opinion matrices are obtained for each DM [18]. However, the most knowledgeable DM is selected, and the opinion matrix of the most knowledgeable DM is defined as Q_k. Other view matrices are symbolized by Q_o. After this classification, the reward degree among DMs is calculated by:

$$RD = r(Q_k - Q_o) \tag{3}$$

Where r means the reward factor. Similarly, the penalty degree among DMs is computed in terms of.

$$PD = p(Q_o - Q_k) \tag{4}$$

Where p represents the penalty factor. Then, the updated opinion matrices are obtained using.

$$Q_u = Q_k + a(RD - PD) \tag{5}$$

Where a is the learning rate. This updating process is applied until the absolute difference between the initial and updated opinion matrix is lower than the threshold value for the convergence.

2.3. Molecular Geometry Analysis

Normalization of molecular fuzzy decision matrix according to molecular geometry shapes is introduced below [19]. Averaged numbers are computed from the balanced fuzzy opinion matrices in terms of.

$$(\bigcup_{i=1}^{d} Q_i) = (\frac{1}{d}\sum_{i=1}^{d} \mu_{Q_i}(u), \frac{1}{d}\sum_{i=1}^{d} v_{Q_i}(u), \frac{1}{d}\sum_{i=1}^{d} \epsilon_{Q_i}(u)) \tag{6}$$

Where d is the number of DMs. Thus, the matrix is obtained.

$$Q = [q_{ij}]_{rxc} \tag{7}$$

Where r is the number of rows and c is the number of columns. In the relation matrix, r and c are equal to each other and the diagonal elements are empty. q is the molecular fuzzy number and equal to the averaged number. Next, each row of this matrix is defined as a fuzzy vector. However, it should be noted that the empty elements of the relation matrix are excluded. The fuzzy vector is identified by:

$$u_i = [(\mu_{i1}, v_{i1}, \epsilon_{i1}), (\mu_{i2}, v_{i2}, \epsilon_{i2}), ...(\mu_{it}, v_{it}, \epsilon_{it})] \tag{8}$$

Where t is the size of fuzzy vector or the number of filled elements in the row of the matrix. In other words, for the relation matrix t is equal to c-1 while for the decision matrix, t is equal to c. Later, the angle between the two fuzzy vectors is estimated using equation:

$$\theta_{u_i,u_j} = cos^{-1}(\frac{\sum_{e=1}^{t}(\mu_{i,e}.\mu_{j,e} + v_{i,e}.v_{j,e} + \epsilon_{i,e}.\epsilon_{j,e})}{(\sum_{e=1}^{t}(\mu_{i,e}^2 + v_{i,e}^2 + \epsilon_{i,e}^2)).(\sum_{e=1}^{t}(\mu_{j,e}^2 + v_{j,e}^2 + \epsilon_{j,e}^2))} \tag{9}$$

Afterwards, the angles are normalized according to molecular geometry shapes or maximum value. This process is defined by function:

$$norm(\theta_{u_i,u_j}) = \begin{cases} \frac{\theta_{u_i,u_j}}{\theta_{max}} \\ \frac{\theta_{u_i,u_j}}{\pi} \\ \frac{\theta_{u_i,u_j}}{\frac{2\pi}{3}} \\ \frac{\theta_{u_i,u_j}}{\frac{\pi}{2}} \\ \frac{\theta_{u_i,u_j}}{\frac{2\pi}{5}} \\ \frac{\theta_{u_i,u_j}}{\frac{\pi}{3}} \end{cases} \tag{10}$$

While the first condition of this function indicates normalization according to the maximum value, the other conditions express normalization according to linear, trigonal planar, tetrahedral, trigonal bipyramidal and octahedral geometric shapes, respectively. Finally, the reciprocal number of the normalized angle is calculated.

$$recip(\theta_{u_i,u_j}) = \frac{1}{norm(\theta_{u_i,u_j})} \tag{11}$$

2.4. Molecular Fuzzy Genetic Algorithms

Using the reciprocal numbers, the normalization of relation matrix is created [20]. The normalization elements are obtained as follows.

$$N_{ij} = \frac{recip(\theta_{u_i,u_j})}{\sum_{j=1}^{n} recip(\theta_{u_i,u_j})} \tag{12}$$

Where n is the number of criteria. Afterwards, initial population including the set of individuals are identified.

$$w = [w_1, w_2, ..., w_n] \tag{13}$$

Similarly, the initial population given information about the collection of individuals is determined by:

$$P = \{w_1, w_2, ..., w_n\} \tag{14}$$

Afterwards, the uniform sampling distribution is used for generating the random numbers between 0 and 1. These numbers are sorted in ascending. After that, the weight is defined to compute the segments by:

$$w_i = r_i - r_{i-1} \tag{15}$$

Where r is the random number. The initial value of r sequence is 0 and the last value of r sequence is 1. The process is applied for all individuals. In another step, the best individuals are determined according to fitness values. This value is calculated in terms of.

$$F(w_i) = \sum_{i=1} \sum_{j=1, j\neq i} (\frac{w_i}{w_j} - \frac{a_{ij}}{a_{ji}})^2 \tag{16}$$

Where a_{ij} is the element of the relation matrix for $C_i$and C_j. Next, the selection and cumulative probabilities are determined.

$$P(w_j) = \frac{F(w_i)}{\sum_{j=1}^{n} F(w_j)} \tag{17}$$

$$CP(w_i) = \sum_{j=1} P(w_j) \tag{18}$$

$$CP(w_i) = \begin{cases} P(w_1) & \text{if } i = 1 \\ CP(w_{i-1}) + P(w_i) & \text{if } i > 1 \end{cases} \tag{19}$$

In other step, the selection process is performed for the individual using a number between 0 and 1.

$$CP(w_{i-1}) < r < CP(w_i) \tag{20}$$

Then, the parent vectors are defined by:

$$PV_1^{(1)} = [w_{1,1}, w_{1,2}, ..., w_{1,c}], PV_1^{(2)} = [w_{1,c+1}, ..., w_{1,n}] \tag{21}$$

$$PV_2^{(1)} = [w_{2,1}, w_{2,2}, ..., w_{2,c}], PV_2^{(2)} = [w_{2,c+1}, ..., w_{2,n}] \tag{22}$$

Where c is the crossover point and identified as $c \in \{1, 2, \ldots, n-1\}$. After that, combining segments are determined as:

$$O_1 = [PV_1^{(1)}, PV_2^{(2)}] = [w_{1,1}, w_{1,2}, ..., w_{1,c}, w_{2,c+1}, ..., w_{2,n}] \tag{23}$$

$$O_1 = [PV_2^{(1)}, PV_1^{(2)}] = [w_{2,1}, w_{2,2}, ..., w_{2,c}, w_{1,c+1}, ..., w_{1,n}] \tag{24}$$

Random changes maintain diversity. Thus, they avoid the premature convergence. Later, the mutated offspring is created by normalized numbers of the offspring:

$$O^{'} = [w_1^{'}, w_2^{'}, ..., w_n^{'}] \tag{25}$$

Where the mutual individuals are computed.

$$w_i^{'} = w_i + \Delta \tag{26}$$

Where Δ is perturbation value and has distribution range between -.05 and .05. Finally, the final fitness score is calculated in terms of.

$$FS(w_i) = \sum_{i=1}^{n}\sum_{j=1}^{n}(N_{ij} - w_i, w_j)^2 \tag{27}$$

2.5. MF-MOPSO

The steps of the process are as follows. The averaged values obtained with Equation (6) are multiplied by the criteria weights obtained with Equation (27), and then a weighted decision matrix is created [21].

$$B_{ij} = (w_j\mu_{ij}, w_j v_{ij}, w_j\epsilon_{ij}) \tag{28}$$

Where w is the weight value. Equations (8) – (11) are used for constructing the reciprocal numbers. Then, the final decision matrix's elements are computed in terms of.

$$f_{ij} = \frac{recip(\theta_{y_i,y_j})}{\sum_{j=1}^{m} recip(\theta_{y_i,y_j})} \tag{29}$$

Where m is the number of the alternatives. The particle presentation is identified by.

$$X_i = \{x_{i1}, x_{i2}, ..., x_{in}\} \tag{30}$$

Afterwards, the velocity of each particle is calculated in terms of.

$$V_{ij}(t+1) = \omega V_{ij}(t) + c_1 r_1(P_{ij}(t) - X_{ij}(t)) + c_2 r_2(P_{gb_j}(t) - X_{ij}(t)) \tag{31}$$

Where $\omega = .5$, $c_1 = c_2 = 1.5$ and $r_{1,2} \in [0, 1]$. In addition initial velocity is defined as:

$$V_{ij}(1) = \partial(P_{max_i} - P_{min_i})r \tag{32}$$

Where $\partial = .1$ and $r \in [-1, 1]$. Then the positions are updated in terms of.

$$X_{ij}(t+1) = X_{ij}(t) + V_{ij}(t+1) \tag{33}$$

The iterative process is continued until $\left|P_{gb_j}(t+1) - P_{gb_j}(t)\right| < .001$. Finally, the average of the positions is computed for ranking.

3. Analysis Results

3.1. Selecting the Relevant Project Alternatives

First, the project alternatives, inputs and outputs are identified. Next, the values of project factors and the lead DM's opinions for project alternatives are provided in Table 1.

Table 1. Project Factors' Values and Lead DM's Opinions

	Project factors				Lead DM Opinion			
Project Alternatives	Resource Efficiency	Carbon Reduction tons/year	Waste Diversion Rate	Return of Investment	Circular Efficiency (CE)	Emission Reduction (ER)	Waste management (WM)	Financial Performance (FP)
Industrial Symbiosis Implementation (ISI)	25	5000	30	18	Significant	Moderate	Moderate	Significant
Waste-to-Energy Plants (WEP)	15	12000	70	22	Low	Significant	High	Significant
Product Life Extension Programs (PLEP)	40	2000	45	15	High	Moderate	Significant	Moderate
Closed-Loop Recycling Systems (CLRS)	50	8000	85	25	High	Significant	High	Significant
Biodegradable Packaging Solutions (BPS)	60	1200	90	12	Significant	Low	High	Moderate
Sustainable Textile Manufacturing (STM)	35	4500	25	20	Moderate	Moderate	Low	Significant
Urban Mining Initiatives (UMI)	45	6500	50	30	Significant	Significant	Moderate	High
Circular Construction Projects (CCP)	55	10000	65	18	High	High	Significant	Significant

Afterwards, the entropies are computed with the help of Equation (1). In another step, the entropies, overall entropies and information gains are calculated using Equation (2). According to results, CE, ER, and WM have the same highest IG in the project factors for CE. In other word, they have the most influential project inputs equally for CE. Similarly, other E and IG are also calculated and shared in Table 2.

Table 2. The IGs for the Project Factors

Resource Efficiency												
	CE			ER			WM			FP		
	E	OE	IG	E	OE	IG	E	OE	IG	E	OE	IG
0-30	1	1.250	.561	1	1	.811	1	1.5	.406	0	1	.299
31-50	1.5			1			2			1.5		
> 51	1			1			1			1		
Carbon Emissions Reduction												
	CE			ER			WM			FP		
	E	OE	IG	E	OE	IG	E	OE	IG	E	OE	IG
0-5000	1.5	1.250	.561	.811	.656	1.156	2	1.5	.406	1	.750	.549
5001-9000	1			0			1			1		
> 9001	1			1			1			0		
Waste Diversion Rate												
	CE			ER			WM			FP		
	E	OE	IG	E	OE	IG	E	OE	IG	E	OE	IG
0-40	1	1.250	.561	0	1	.811	1	1	.906	0	0	.299
41-70	1.5			1.5			1.5			1.5		
> 71	1			1			0			1		
Return of Investment												
	CE			ER			WM			FP		
	E	OE	IG	E	OE	IG	E	OE	IG	E	OE	IG
0-15	1	1.451	.360	1	1.201	.610	1	1.451	.454	0	0	1.299
16-25	1.922			1.522			1.922			0		
> 26	0			0			0			0		

It is identified that CE, ER and WM has the maximum value for CE, ER is the most important project specification for ER, and WM has the best influential input for WM, and FP has the best IG for FP. The scales with the maximum positive numbers are determined for the most influential project specifications. The reduced project alternatives are obtained as WEP, CLRS, BPS, UMI, and CCP for circular-oriented projects in sustainable investments.

3.2. Constructing the balanced DMs' Opinion Matrices

Decision criteria and reduced project alternatives for circular-oriented project investments are evaluated by DMs. These opinions are transformed to molecular fuzzy numbers. DM 1 is the lead DM because of experience. The experience periods of DMs are 25, 15 and 15, respectively. For this reason, the weights of DMs are 0.5, 0.25 and 0.25, respectively. These weights are used for reward and penalties factors. The reward degrees are computed using Equation (3). Similarly, the penalty degrees for two matrices are calculated with the help of Equation (4). Afterwards, the updated opinion matrices are obtained by Equation (5). Next, the convergence is tested. For this, the threshold value is determined as .02. Convergence is achieved as a result of the fifth iteration. In this case, the balanced opinion matrices are given in Table 3.

Table 3. The IGs for the Project Factors

DM 1	CE	ER	WM	FP
CE	(.00, .00, .00)	(.60, .30, .10)	(.95, .05, .00)	(.95, .05, .00)
ER	(.80, .15, .05)	(.00, .00, .00)	(.80, .15, .05)	(.95, .05, .00)
WM	(.95, .05, .00)	(.80, .15, .05)	(.00, .00, .00)	(.80, .15, .05)
FP	(.95, .05, .00)	(.80, .15, .05)	(.95, .05, .00)	(.00, .00, .00)
DM 2	CE	ER	WM	FP
CE	(.00, .00, .00)	(.60, .30, .10)	(.95, .05, .00)	(.95, .05, .00)
ER	(.80, .15, .05)	(.00, .00, .00)	(.80, .15, .05)	(.90, .08, .02)
WM	(.84, .13, .03)	(.80, .15, .05)	(.00, .00, .00)	(.80, .15, .05)
FP	(.84, .13, .03)	(.74, .20, .07)	(.95, .05, .00)	(.00, .00, .00)
DM 3	CE	ER	WM	FP
CE	(.00, .00, .00)	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)
ER	(.80, .15, .05)	(.00, .00, .00)	(.80, .15, .05)	(.95, .05, .00)
WM	(.80, .15, .05)	(.80, .15, .05)	(.00, .00, .00)	(.80, .15, .05)
FP	(.95, .05, .00)	(.80, .15, .05)	(.95, .05, .00)	(.00, .00, .00)
DM 1	CE	ER	WM	FP
WEP	(.60, .30, .10)	(.60, .30, .10)	(.95, .05, .00)	(.80, .15, .05)
CLRS	(.95, .05, .00)	(.80, .15, .05)	(.95, .05, .00)	(.80, .15, .05)
BPS	(.95, .05, .00)	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)
UMI	(.60, .30, .10)	(.80, .15, .05)	(.80, .15, .05)	(.95, .05, .00)
CCP	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)
DM 2	CE	ER	WM	FP
WEP	(.71, .22, .07)	(.71, .22, .07)	(.95, .05, .00)	(.85, .12, .03)
CLRS	(.95, .05, .00)	(.80, .15, .05)	(.95, .05, .00)	(.80, .15, .05)
BPS	(.95, .05, .00)	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)
UMI	(.60, .30, .10)	(.80, .15, .05)	(.80, .15, .05)	(.95, .05, .00)
CCP	(.80, .15, .05)	(.85, .12, .03)	(.80, .15, .05)	(.85, .12, .03)
DM 3	CE	ER	WM	FP
WEP	(.60, .30, .10)	(.80, .15, .05)	(.95, .05, .00)	(.80, .15, .05)
CLRS	(.95, .05, .00)	(.80, .15, .05)	(.95, .05, .00)	(.80, .15, .05)
BPS	(.95, .05, .00)	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)
UMI	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)
CCP	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)

3.3. Weighting the Decision Criteria

The averaged relation numbers are obtained. The averaged relation numbers in Equation (7) are shared in Table 4.

Afterwards, the fuzzy vectors for RM are identified according to Equation (8). In another step, the angles between any two fuzzy vectors for RM are computed by Equation (9). The relation angles are illustrated in Table 5

Table 4. Averaged Relation Numbers

	CE	ER	WM	FP
CE		(.67, .25, .08)	(.90, .08, .02)	(.90, .08, .02)
ER	(.80, .15, .05)		(.80, .15, .05)	(.93, .06, .01)
WM	(.86, .11, .03)	(.80, .15, .05)		(.80, .15, .05)
FP	(.91, .08, .01)	(.78, .17, .06)	(.95, .05, .00)	

Table 5. The Relation Angles

	θ_{u_1}	θ_{u_2}	θ_{u_3}	θ_{u_4}
θ_{u_1}		.145	.208	.228
θ_{u_2}	.145		.123	.087
θ_{u_3}	.208	.123		.116
θ_{u_4}	.228	.087	.116	

The normalized relation angles are obtained according to shapes. Finally, the reciprocal numbers are calculated with Equation (11). Next, the normalization of relation matrix is created using Equation (12). Equations (13) and (14) are used for creating the initial population. After that, the weight is computed the segments by Equation (15). This fitness value is calculated using Equation (16). Then, probabilities are computed with Equations (17)-(19). In other step, the selection process is performed for the individual with Equation (20). Then, the parent vectors are defined by Equations (21) and (22). After that, combining segments are determined with Equations (23) and (24). Later, the mutated offspring is created by normalized numbers of the offspring with the help of Equation (25). The mutual individuals are computed by Equation (26). Finally, the final fitness score is calculated using Equation (27). The mutated offspring are FFS are shared in Table 6.

Table 6. The Mutated Offspring and Final Fitness

Weights					FFS
Mutated Offspring 1 (Perturbation:-.02)	.105	.348	.421	.105	.2442
Mutated Offspring 2 (Perturbation:+.03)	.220	.286	.257	.267	.1747
Mutated Offspring 3 (Perturbation:+.05)	.111	.389	.328	.222	.1880
Mutated Offspring 4 (Perturbation:-.01)	.136	.364	.245	.245	.1768

Offspring 2 is determined as the most important decision criteria. Accordingly, the weights of the decision criteria are computed as 0.220 for CE, 0.286 for ER, 0.257 for WM, 0.267 for FP. The comparative output for weighting is illustrated in Table 7.

Table 7. The Comparative Output for Weighting

.1	F2	F3	F4	F5	F6	.5	F2	F3	F4	F5	F6	1	F2	F3	F4	F5	F6
CE	4	4	4	4	4	CE	4	4	4	4	4	CE	4	4	4	4	4
ER	1	1	1	1	1	ER	1	1	1	1	1	ER	1	1	1	1	1
WM	3	3	3	3	3	WM	3	3	3	3	3	WM	3	3	3	3	3
FP	2	2	2	2	2	FP	2	2	2	2	2	FP	2	2	2	2	2

3.4. Ranking the Project Alternatives

The averaged decision numbers are obtained. The averaged decision numbers in Equation (7) are shared in Table 8.

Table 8. The Averaged Decision Numbers

	CE	ER	WM	FP
WEP	(.64, .27, .09)	(.70, .22, .07)	(.95, .05, .00)	(.82, .14, .04)
CLRS	(.95, .05, .00)	(.80, .15, .05)	(.95, .05, .00)	(.80, .15, .05)
BPS	(.95, .05, .00)	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)
UMI	(.67, .25, .08)	(.80, .15, .05)	(.80, .15, .05)	(.90, .08, .02)
CCP	(.80, .15, .05)	(.82, .14, .04)	(.80, .15, .05)	(.82, .14, .04)

Equation (28) is used to create a weighted decision matrix. Equations (8) – (11) are used for constructing the reciprocal numbers. Then, the final decision matrix's elements are computed by Equation (29). The final decision matrix for F2 is displayed in Table 9.

Table 9. The Comparative Output for Ranking

	WEP	CLRS	BPS	UMI	CCP
WEP		0.073	0.06	0.095	0.08
CLRS	0.073		0.147	0.069	0.112
BPS	0.06	0.147		0.075	0.155
UMI	0.095	0.069	0.075		0.134
CCP	0.08	0.112	0.155	0.134	

Afterwards, Equations (30)-(33) are used for updating the best positions. It is concluded that condition is met in fourth round. Thus, the averages of the positions are obtained as 0.1447, 0.1324, 0.1316, 0.1383, and 0.1343 respectively. The comparative output is shown in Table 10.

Table 10. The Final Decision Matrix for F2

0.1	F2	F3	F4	F5	F6	0.5	F2	F3	F4	F5	F6	1	F2	F3	F4	F5	F6
WEP	1	1	1	1	1	WEP	1	1	1	1	1	WEP	1	1	1	1	1
CLRS	4	4	4	4	4	CLRS	4	4	4	4	4	CLRS	4	4	4	4	4
BPS	5	5	5	5	5	BPS	5	5	5	5	5	BPS	5	5	5	5	5
UMI	2	2	2	2	2	UMI	2	2	2	2	2	UMI	2	2	2	2	2
CCP	3	3	3	3	3	CCP	3	3	3	3	3	CCP	3	3	3	3	3

As can be seen from Table 17, the ranking of projects according to different learning rates and shapes is the same, indicating the consistency and validity of the outputs.

4. Conclusions

This study satisfies an important gap in the literature regarding the identification of key performance indicators of circular-oriented project investments. A new model is recommended while integrating information gain for project prioritization, Q-learning for expert evaluation, genetic algorithms for criteria weighting, and swarm optimization for alternative ranking. The findings indicate that emission reduction and financial performance are the most crucial factors in improving the performance of circular-oriented projects. Furthermore, the study highlights waste-to-energy plants and urban mining initiatives as the most significant project alternatives for driving circular economy investments. Hence, governments should offer financial incentives to prioritize emission reductions. Moreover, introducing carbon taxes can make emission reductions more financially attractive. Similarly, governments should foster collaborations between public and private sectors to support the transition to circular economy models. One of the major limitations of this study is the reliance on expert evaluation. This situation creates a subjectivity problem. Hence, to solve this problem, in the following studies, comprehensive and high-quality data from real-world circular economy projects can be considered.

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