atmosphere

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Multi-Criteria Decision Analysis for Optimizing CO_2 and NH_3 Removal by *Scenedesmus dimorphus* Photobioreactors

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Abstract: Numerous technologies have been investigated for mitigating air pollutant emissions from swine barns. Among them, algal photobioreactors (PBRs) can remove and utilize air pollutants such as CO_2 and NH_3 from barn exhaust. However, a challenge to PBR operation is that it involves multiple system input parameters and output goals. A key question is then how to determine the appropriate CO_2 and NH_3 concentrations in this case. Conventional statistical methods are inadequate for handling this complex problem. Multi-criteria decision-making (MCDM) emerges as a practical methodology for comparison and can be utilized to rank different CO_2–NH_3 interactions based on their environmental and biological performance. By employing MCDM methods, producers can effectively control the ratio of CO_2 and NH_3 concentrations, enabling them to identify the optimal range of operating parameters for various housing types, ensuring efficient pollutant mitigation. In this study, a multi-criteria decision-making (MCDM) approach was employed to support operation management. Specifically, influent CO_2 and NH_3 concentrations were optimized for three scenarios (the best biological, environmental, and overall performance), using a combination of two MCDM techniques. This study is anticipated to facilitate the system analysis and optimization of algae-based phytoremediation processes.

Keywords: CILOS; GRA; multi-criteria decision-making; swine barns; *Scenedesmus dimorphus*; algae

Citation: Uguz, S.; Arsu, T.; Yang, X.; Anderson, G. Multi-Criteria Decision Analysis for Optimizing CO_2 and NH_3 Removal by *Scenedesmus dimorphus* Photobioreactors. *Atmosphere* **2023**, *14*, 1079. https://doi.org/10.3390/atmos14071079

Academic Editors: Zhangliang Han and Zhiping Ye

Received: 31 May 2023
Revised: 17 June 2023
Accepted: 23 June 2023
Published: 27 June 2023

1. Introduction

Concentrated animal production results in significant air pollutant emissions that contribute to environmental pollution and global warming issues. Various air pollutants, such as NH_3, H_2S, CH_4, and CO_2, can originate from animal housing, manure storage, and land application [1]. There is a need to mitigate these pollutants while sustaining animal protein supplies. This mitigation will not only protect the environment but also improve indoor air quality critical for animal health and welfare, as well as the safety and health of farm workers [2,3].

Various mitigation technologies/practices have been researched, including air scrubbers, biofilters, tree barriers, diet manipulation, and improved manure management [4–6]. Among them, CO_2 and NH_3 fixation by microalgal photosynthesis has recently attracted significant attention due to its eco-friendliness and potential economic benefits. Microalgae have substantially higher cell growth and CO_2 fixation rates (about 10–50 times) than terrestrial plants [7]. They can be further valorised into biofuels, animal feed, nutrition additives, cosmetics, and pharmaceuticals [8].

Numerous factors play a crucial role in effectively reducing air pollutants released from animal barns using photobioreactor (PBR) systems. The concentrations of air pollutants vary depending on the livestock breed, animal age, and barn type. Similarly, the growth of microalgae in PBR systems differs in terms of their air pollutant reduction efficiency, biomass yield, and cell growth, which are influenced by the emitted CO_2 and NH_3 gas concentrations from the barn. Therefore, to achieve optimal CO_2 and NH_3 gas reduction efficiencies, it is essential to determine the gas concentrations at which microalgae exhibit the best cell growth and biomass yield. The existing literature indicates that while the highest cell growth, measured by cell counts, can occur at any CO_2 gas concentration, the maximum biomass yield may be obtained at a different gas concentration [9]. A microalga that demonstrates the highest cell growth at a specific CO_2 gas concentration might exhibit lower cell growth at another CO_2 concentration due to the presence of NH_3 gas in the PBR system, where CO_2 and NH_3 gases coexist [10]. In other words, although cell growth reaches its peak at a given CO_2 gas concentration, the maximum biomass yield may not be achieved at the same CO_2 gas concentration. Therefore, for the most effective mitigation of air pollutants released from animal barns using PBR systems, it is crucial to collectively evaluate and analyze the biological and environmental parameters that influence microalgae growth. By doing so, maximum efficiency can be obtained from all parameters influencing algal growth, and identifying the air pollutant concentrations at which the highest gas reduction efficiency can be achieved will enhance the system's effectiveness and economic viability.

Challenges exist to effective CO_2 and NH_3 gas mitigation with microalgae due to the complexity of the relevant processes. For example, CO_2 and NH_3 fixation efficiencies can be affected by many operating parameters, such as gas loading rates, gas concentrations, pH, light intensity, and temperature. Numerous studies have been conducted to examine the effects of these parameters [8,11–13]. In nearly all these studies, different parameters were examined separately. However, interactions between the parameters should not be neglected. For example, Kang and Wen [14] reported that the solubility and uptake of CO_2 by algae were affected by the presence of NH_3 in PBRs. Moreover, algal PBRs for air pollutant mitigation (and other phytoremediation purposes) often involve multiple system input parameters (e.g., CO_2 concentrations, pH, and temperature) and multiple output goals (e.g., biomass yield and NH_3 removal efficiency), making it challenging to make management decisions concerning algal PBR operation. Previous studies have highlighted the challenge of CO_2 concentration when utilizing microalgae for pollutant capture. Traditional statistical methods may not be adequate for addressing the complexities associated with determining suitable CO_2 and NH_3 concentrations for algal growth. Therefore, prioritizing the options for mitigating pollutants through CO_2 and NH_3 concentration requires a multi-criteria approach. One practical methodology for comparison in this regard is multi-criteria decision-making (MCDM). In this paper, a multi-criteria assessment model is proposed which combines grey relational analysis (GRA) and criterion impact loss (CI-LOS) techniques. This model allows for the ranking of different CO_2–NH_3 interactions based on their environmental and biological performance. By applying the CI-LOS method, objective determination of weights can be achieved for parameters such as cell number, biomass yield, and others that monitor microalgae growth, as well as parameters indicating gas reduction efficiency. Subsequently, using the GRA method and considering these weights, the optimal CO_2 and NH_3 gas concentrations can be determined.

Advancements in decision-making sciences have made MCDM methods increasingly accessible and accepted recently. MCDM refers to decision-making in the presence of multiple criteria that are inconsistent or even contradictory [15]. It is particularly useful for systems with multiple criteria and alternatives. The development of MCDM methods is motivated by not only various real-life problems requiring the consideration of multiple criteria but also by advances in mathematical optimization, scientific computing, and computer technology [16]. A fundamental task of MCDM is to evaluate a set of alternatives with a set of criteria. This involves the determination of the criteria that can be organised according to the expectation of a decision to be made for possibly solving a problem and other alternatives [17].

MCDM has been used in solving various problems in social sciences such as supplier selection [18–20], financial performance [21,22], and cyber security [23,24], as well as in engineering and science problems such as geographic information systems [25,26], construction equipment evaluation [27,28], and machine tool selection [29,30]. This method has been applied successfully in environmental research areas, from optimising waste management systems [31] to selecting gas mitigation methods [32,33]. Only a few reports are available concerning its applications for algal research, with the majority focusing on harvesting technologies [34,35]. Others include the identification of the best microalgae strain for biodiesel production [36], the best areas for microalgal cultivation [37], and the best algal wastewater treatment systems [38]. To our knowledge, no application of MCDM for algal PBR operation has been reported.

This study presents the first such attempt to identify optimal NH_3 and CO_2 concentrations for algal PBR operation. The primary aim of using the multi-criteria analysis is to find the relative importance of the factors and the criteria that affect cultivation of *S. dimorphus* with gas concentrations typical of pig house exhaust air. As a restriction, the specified concentrations must be within the typical concentration range of swine barn exhaust. The optimization was conducted to maximize the (1) biological, (2) environmental, and (3) overall performance of algal PBR systems. For each of the system output goals (scenarios), multiple performance indicators were considered. Specifically, the biological performance (i.e., algal growth) was measured by algal cell concentration, dry algal biomass, maximum specific growth rate, and cell weight; the environmental performance (i.e., pollutant mitigation) was measured by CO_2 fixation rate, NH_3 fixation efficiency, CO_2 removal efficiency, and NH_3 removal efficiency; and the overall performance was measured by all the indicators stated above. Sixteen experimental data sets were analyzed with two MCDM methods (criterion impact loss (CILOS) and grey relational analysis (GRA)) following the multi-step procedure outlined in Figure 1. Such optimization cannot be performed with regular statistical tools.

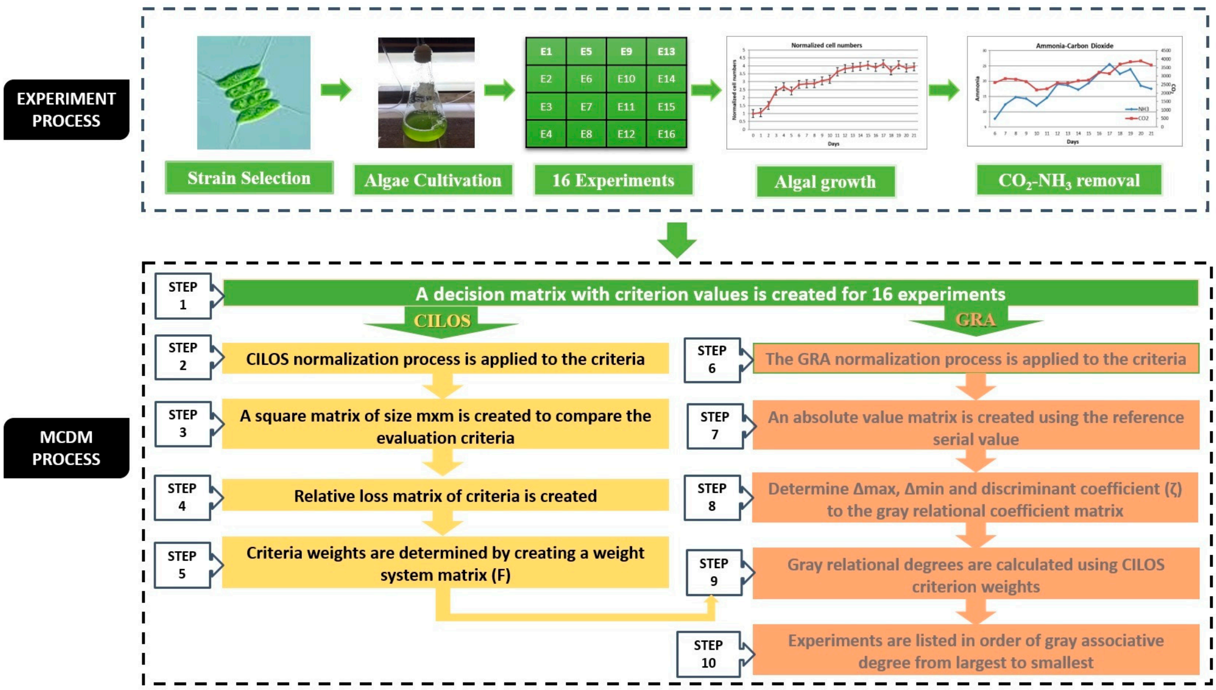

Figure 1. Workflow chart for proposed MCDM analyses.

2. Materials and Methods

2.1. Experimental Prodecure

Scenedesmus dimorphus (*S. dimorphus*) strain UTEX 1237 was cultivated in 1 L Erlenmeyer flasks containing 100 mL of Bold's basal medium with the composition of Uguz et al. [24]. This strain was used because of its efficient CO_2 and NH_3 removal [24].

The prepared BBM was sterilised and placed in the autoclave for 20 min at 121 °C. The cultures were doubled weekly and then transferred to 5 L PBRs when they reached the 5 L working volume for testing. The PBRs were built from acrylic plastic sheets sized 35 cm (height) × 50 cm (length) × 10 cm (width). Figure 2 shows the PBR experiment in operation.

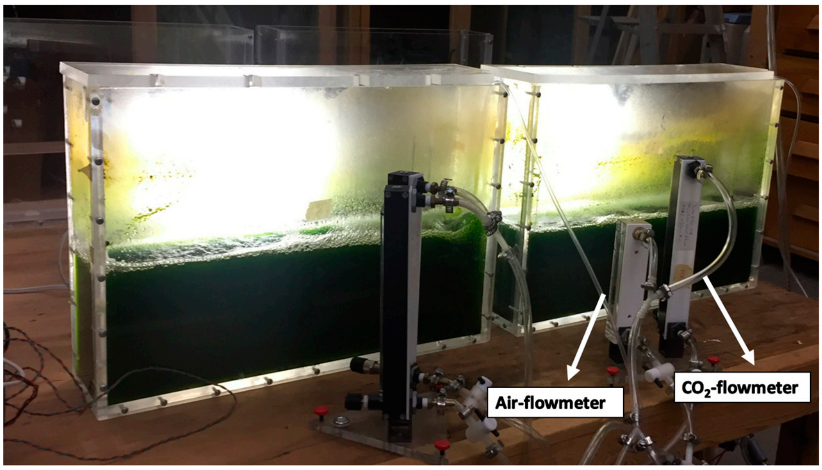

Figure 2. PBRs operating in the experiment.

Following the cultivation, 16 experiments were conducted in the laboratory under controlled conditions. In brief, algal PBRs were filled with a 5 L cultivation medium, fed with CO2-laden air at an airflow rate of 5 L min^{-1}, and illuminated at a 60–65 µmol s^{-1} m^{-2} light density. CO_2 concentration in the influent air (Table 1) was regulated using rotameters (Cole Parmer, Vernon, IL, USA) with needle valves. For NH_3, due to its strong adsorption along tubings and adaptors, no rotameter-dilution method was used. Instead, ammonium chloride (NH_4Cl) was added daily to the cultivation medium as an alternative NH_3 source. It was calculated that the NH_4Cl daily doses of 0, 19, 39, and 78 mg $L^{-1}d^{-1}$ would be equivalent to the aerial NH_3 concentrations of 0, 12, 25, and 50 ppm, respectively, in the influent air. Other parameters, such as pH, temperature, and lighting, were constant throughout the cultivation experiments. The experiments were performed in triplicate, with control PBRs (fed with no NH_3 or CO_2) available for comparison. CO_2 and NH_3 gas concentrations were monitored using an INNOVA 1314i photoacoustic multi-gas monitor 1314i (LumaSense Technologies A/S, Ballerup, Denmark).

2.2. Analytical Methods

A detailed description can be found in Uguz et al. [39]. In brief, algal samples harvested from the sixteen experiments were analyzed for cell concentration (cells L^{-1}), dry algal biomass concentration (mg L^{-1}), cell weight (mg $cell^{-1}$), specific growth rate (d^{-1}), CO_2 fixation efficiency (mg L^{-1} d^{-1}), NH_3 fixation efficiency (mg L^{-1} d^{-1}), CO_2 removal efficiency (%), and NH_3 removal efficiency (mg L^{-1} d^{-1}). The cell concentration was measured using haemocytometers under an Olympus optical microscope. The dry algal biomass concentration was gravimetrically determined by vacuum-filtering a known volume of an algal sample and weighing the filter after being dried in a laboratory oven at 80 °C for 3 h [40,41]. The cell weight was calculated by dividing a dry algal biomass concentration by its corresponding cell concentration. The specific growth efficiency was calculated by normalizing a cell concentration increase with the initial cell concentration. The NH_3 and CO_2 fixation efficiencies of the algae were calculated by multiplying the growth rate of algal biomass by nitrogen and carbon contents (%wt) in *S. dimorphus*. The NH_3 and CO_2 removal efficiencies were calculated by dividing their fixation efficiencies (mg L^{-1} d^{-1}) by their loading rates (mg L^{-1} d^{-1}) to the PBRs.

Table 1. Criteria and key performance indicators to evaluate the performance of algal PBRs.

Criteria	Key Performance Indicators (Kpis)		Definition
Biological Performance	C1	Cell count	Indicating algal cell concentrations grown with NH_3 and CO_2 typical of the barn exhaust air
	C2	Dry biomass	Indicating algal dry biomass concentrations grown with NH_3 and CO_2 typical of the barn exhaust air
	C3	Cell weight	Indicating average algal cell weight grown with NH_3 and CO_2 typical of the barn exhaust air
	C4	Growth rate	Indicating specific algal growth rate, i.e., a ratio of algal cell increase to the initial cell concentration.
Environmental Performance	C5	CO_2 fixation rate	Indicating CO_2 uptake by algae—an estimate from algal biomass and its carbon content
	C6	NH_3 fixation rate	Indicating NH_3 uptake by algae—an estimate from algal biomass and its nitrogen content
	C7	CO_2 removal rate	Indicating the fraction of CO_2 in PBR influents taken up by algae
	C8	NH_3 removal rate	Indicating the fraction of NH_3 in PRB influents taken up by algae
Overall Performance	C1, C2, C3, C4, C5, C6, C7 and C8		

2.3. Multi-Criteria Analyses

In the study, sixteen experiments with different combinations of CO_2 and NH_3 gas concentrations were conducted. At the end of each experiment, cell number, dry weight, cell weight, growth rate, CO_2 and NH_3 fixation and removal rates were calculated to monitor algal growth and CO_2 and NH_3 mitigation efficiencies. These parameters were chosen as criteria for the MCDM analysis of the experiments. Then, the weights of each criterion were determined using the CILOS method. Figure 1 shows the weight of each selected criterion in CILOS method. The derived weight numbers then served as input to GRA. As aforementioned, the analyses compared three scenarios/output goals, with each scenario involving multiple performance indicators (Table 1). The indicator data derived from algal cultivation experiments (sixteen batches) are summarized in Table 2.

Table 2. Decision matrix for multi-criteria analyses.

Scenarios	**NH_3-CO_2 Combinations**	**Overall Performance**							
		Biological Performance				**Environmental Performance**			
Criteria Aspects		**Max**	**Max**	**Max**	**Max**	**Max**	**Max**	**Max**	**Max**
Criteria/Indicators		**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
EXP1	0 ppm NH_3-350 ppm CO_2	0.54	0.60	0.31	3.39	0	0	0	0
EXP2	12 ppm NH_3-350 ppm CO_2	1.15	1.12	0.44	0.96	99.5	22.3	5.48	76.6
EXP3	25 ppm NH_3-350 ppm CO_2	1.27	1.20	0.6	2.08	81.8	18.3	4.5	36.1
EXP4	50 ppm NH_3-350 ppm CO_2	1.23	1.24	0.45	2.26	71.0	15.9	3.9	15.6
EXP5	0 ppm NH_3-1200 ppm CO_2	0.69	0.72	0.05	1.28	0	0	0	0
EXP6	12 ppm NH_3-1200 ppm CO_2	1.78	1.80	0.35	1.01	193.0	12.6	10.6	94.4
EXP7	25 ppm NH_3-1200 ppm CO_2	1.95	2.00	0.62	0.53	364.8	23.8	20.1	85.3
EXP8	50 ppm NH_3-1200 ppm CO_2	1.41	1.45	0.26	1.2	128.7	8.4	7.09	28.4
EXP9	0 ppm NH_3-2350 ppm CO_2	0.85	0.88	0.28	1.73	6.30	0.41	0.34	0

Table 2. *Cont.*

Scenarios	NH_3-CO_2 Combinations	Overall Performance							
		Biological Performance				Environmental Performance			
Criteria Aspects		Max	Max	Max	Max	Max	Max	Max	Max
Criteria/Indicators		C1	C2	C3	C4	C5	C6	C7	C8
EXP10	12 ppm NH_3-2350 ppm CO_2	1.76	1.77	0.34	1.06	163.8	5.46	9.02	80.0
EXP11	25 ppm NH_3-2350 ppm CO_2	2.04	2.16	0.43	0.58	432.2	14.4	23.8	99.8
EXP12	50 ppm NH_3-2350 ppm CO_2	1.32	1.33	0.35	0.73	252.9	8.43	13.9	55.7
EXP13	0 ppm NH_3-3500 ppm CO_2	1.17	1.19	0.31	1.26	54.4	1.21	2.99	0
EXP14	12 ppm NH3-3500 ppm CO_2	2.21	2.22	0.49	0.75	267.3	5.98	14.7	97.2
EXP15	25 ppm NH3-3500 ppm CO_2	1.56	1.53	0.83	1.58	105.8	2.36	5.83	46.7
EXP16	50 ppm NH_3-3500 ppm CO_2	1.21	1.23	0.51	1.23	105.6	2.36	5.81	23.3

All criteria in the decision matrix were maximization-oriented criteria for all three scenarios. Each NH_3-CO_2 combination corresponded to a unique set of input and output data.

2.3.1. Criteria Impact Loss (CILOS)

The CILOS method, the theoretical background created by Mirkin (1974) and the detailed algorithm presented by Zavadskas and Podvezko [42] are among the most promising approaches to determining the objective weight. The CILOS method considers each criterion's loss of importance (impact) when one of the other criteria achieves the optimal maximum or minimum value. The stages and calculation algorithm of the CILOS method are briefly described below [42–46]:

Step 1. Creating a decision matrix

The CILOS method starts with a decision matrix. The decision matrix of $m \times n$ size, which includes m criteria and n alternatives, is named Z and shown in Equation (1). Here, r_{12} denotes the 2nd criterion value of the 1st alternative, while r_{21} denotes the 1st criterion score of the 2nd alternative.

$$Z = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{pmatrix} \tag{1}$$

Step 2. Converting cost criteria into benefits

Since the CILOS method only provides solutions for maximization-oriented criteria, Equation (2) is used to transform the minimization-oriented criteria into maximization-oriented (best). There is no minimization-oriented criterion for algal growth in this paper.

$$\bar{r}_{ij} = \frac{min_i r_{ij}}{r_{ij}} \tag{2}$$

where r_{ij} is the cost-oriented criterion showing the i alternative value of the j criterion. On the other hand, $\bar{r}_{ij}$ is the cost-oriented criterion transformed into a benefit-oriented criterion.

Step 3. Normalization

Equation (3) is applied to each criterion value for normalization. After normalization, a new matrix X is obtained.

$$\bar{x}_{ij} = \frac{r_{ij}}{\sum_{i=1}^{n} r_{ij}} \tag{3}$$

where, x_i^* is the normalized criterion value

Step 4. Creating a square matrix (A)

After obtaining the normalized X matrix, a square matrix (A) is derived with Equations (4) and (5). The row containing the $\max_i r_{ij}$ element with the maximum value in each column is processed as in Equation (5) to form a square matrix. That is, the square matrix is obtained by taking the row with the maximum element in the ith column of the normalized decision matrix as the new matrix ith row.

$$a_j = \max_i r_{ij} = a_{k_i j} \tag{4}$$

$$a_{ij} = a_{k_i j} \text{ and } a_{jj} = a_j \tag{5}$$

where $a_{k_i j}$ specifies the maximum values of jth criteria, which are taken from the decision matrix with k_i rows to form a square matrix, $a_{ij} = a_{k_i j}$ and $a_{jj} = a_j$ [47].

Step 5. Calculating a relative loss of impact matrix (P)

The values in the square matrix A are processed by Equation (6) to form the relative loss of effect matrix $P = \|p_{ij}\|$.

$$p_{ij} = \frac{a_{jj} - a_{ij}}{a_{jj}}, \quad (p_{ii} = 0;\ i, j = 1, 2, 3, \ldots, m) \tag{6}$$

In matrix P, p_{ij} represents the loss of effect in the jth criterion when the ith criterion is selected as the best.

Step 6. Determining a weight system matrix *(F)*

The F matrix in Equation (7) is formed by finding the sum of each column of the P matrix and writing the negative values of these sums on the diagonals of the P matrix.

$$F = \begin{pmatrix} -\sum\limits_{i=1}^{m} p_{i1} & p_{12} & \cdots & p_{1m} \\ p_{21} & -\sum\limits_{i=1}^{m} p_{i2} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & -\sum\limits_{i=1}^{m} p_{im} \end{pmatrix} \tag{7}$$

Step 7. Calculation of weight of each criterion

The final criterion weights ($q = q_1, q_2, \ldots, q_m$) are determined by solving Equation (8) (using Excel 2016 or Matlab 9.13).

$$Fq^T = 0 \tag{8}$$

The weights q of the criteria are obtained by solving the equation $Fq^T = 0$. Since this system of equations has infinite solutions, the weight vector is determined by normalizing the values so that $\sum_{i=1}^{m} q_i = 1$.

2.3.2. Grey Relational Analysis (GRA)

Grey system theory, a control theory first proposed by Deng [48], has significantly impacted numerous fields of engineering and management. The theory enabled the development of grey relational analysis (GRA), a powerful tool that can effectively resolve complex relationships between multiple performance characteristics through the optimization of grey relational degrees [49].

As in almost all MCDM methods, GRA problem solving starts with a decision matrix consisting of the values of decision criteria. Since the decision matrix is created in the same way as CILOS (Equation (1)), no further explanation is given in this section. The problem solving procedure of GRA is summarized below [49–53]:

Step 1. Creating a comparison matrix

Equation (9) is used to calculate a reference series in the comparison matrix (for criteria comparison).

$$x_o = (x_0(1), x_0(2), \ldots, x_0(j))\ j = 1, 2, \ldots, n \tag{9}$$

where $X_0(j)$ represents the optimal value of the jth criterion within the normalized values. This series is obtained by taking the best value of each criterion in the decision matrix.

Step 2. Normalization and creating of normalized decision matrix

Decision problems, by their nature, consist of criteria with different units and objectives. Therefore, a normalization process is adopted while solving the decision problems. There are three possible situations for normalization in the GRA method.

i. The Larger-The-Better Case: If the criterion used is of the highest appropriateness for the purpose, normalization is performed using Equation (10).

$$x_i^* = \frac{x_i(j) - \min_j x_i(j)}{\max_j x_i(j) - \min_j x_i(j)} \tag{10}$$

ii. The Smaller-The-Better Situation: If the criterion used is of the smallest appropriateness for the purpose, normalization is performed using Equation (11).

$$x_i^* = \frac{\max_j x_i(j) - x_i(j)}{\max_j x_i(j) - \min_j x_i(j)} \tag{11}$$

where, x_i^* is the normalized criterion value, and $x_i(j)$ is the value of the jth criterion in the initial decision matrix.

iii. The Closer-To-The-Desired-Value-The-Better Situation: If the criterion used is of the optimal appropriateness (the most suitable) for the purpose, normalization is performed using Equation (12).

$$x_i^* = \frac{|x_i(j) - x_{0b}(j)|}{\max_j x_i(j) - x_{0b}(j)} \tag{12}$$

where $x_{0b}(j)$ is the determined optimal value, and jth indicates the target value of the criterion. This optimal value can take a value in the range $\min_j x_i(j) \le x_{0b}(j) \le \max_j x_i(j)$. After completion of the normalization process, a normalized decision matrix is obtained. The normalized decision matrix (X^*) of $m \times n$ size, which includes m criteria and n alternatives, is shown in Equation (13).

$$X^* = \begin{bmatrix} x_1^*(1) & x_1^*(2) & \dots & x_1^*(n) \\ x_2^*(1) & x_2^*(2) & \dots & x_2^*(n) \\ \vdots & \vdots & \ddots & \vdots \\ x_m^*(1) & x_m^*(2) & \dots & x_m^*(n) \end{bmatrix} \tag{13}$$

Step 3. Calculating an absolute value matrix

The normalized values of the decision matrix are subtracted from the normalized values of the reference series (Equation (14)) to form an absolute value matrix (Equation (15)).

$$\Delta_{0i} = x_0^*(j) - x_i^*(j) \tag{14}$$

$$\Delta_{0i} = \begin{bmatrix} \Delta_{01}(1) & \Delta_{01}(2) & \dots & \Delta_{01}(n) \\ \Delta_{02}(1) & \Delta_{02}(2) & \dots & \Delta_{02}(n) \\ \vdots & \vdots & \ddots & \vdots \\ \Delta_{0m}(1) & \Delta_{0m}(2) & \dots & \Delta_{0m}(n) \end{bmatrix} \tag{15}$$

where Δ_{0i} represents the values of the absolute value matrix.

Step 4. Creating a grey relational coefficient matrix

Equation (16) is used to create the grey relational coefficient matrix in which Δ_{max} and Δ_{min} are calculated with Equations (17) and (18), respectively.

$$\gamma_{0i}(j) = \frac{\Delta_{min} + \zeta.\Delta_{max}}{\Delta_{0i}(j) + \zeta.\Delta_{max}} \tag{16}$$

$$\Delta_{max} = \max_i \max_j \Delta_{0i}(j) \tag{17}$$

$$\Delta_{min} = \min_i \min_j \Delta_{0i}(j) \tag{18}$$

where $\gamma_{0i}(j)$ represents the values of the grey relational coefficient matrix. The "discriminant coefficient" or "contrast control coefficient" ζ in Equation (14) is a value in the range of [0, 1]. To be consistent with the literature, ζ = 0.5 was taken in this study for relevant analyses.

Step 5. Calculating grey relational degrees

The grey relational degree is a measure of the geometric similarity between the x_i^* series in a grey system and the reference series x_0^* and allows the series to be compared. A large grey relational degree indicates a strong relationship between the comparative and reference series. If the two series being compared are identical, the grey correlation degree is 1.

The calculation of grey relational degrees differs according to the weight status of the criteria. When criteria weights are all equal, the grey relational degrees are calculated with Equation (19), while Equation (20) is used when criterion weights differ.

$$\Gamma_{0i} = \frac{1}{n}\sum_{j=1}^{n} \gamma_{0i}(j) \tag{19}$$

$$\Gamma_{0i} = \sum_{j=1}^{n} [w_i(j).\gamma_{0i}(j)] \tag{20}$$

where Γ_{0i} refers to the grey relational degrees, and $w_i(j)$ is the weight of the jth criterion. The sum of the criterion weights must be equal to 1 ($\sum_{j=1}^{n} w_j = 1$).

3. Results and Discussion

3.1. Biological Performance

When evaluating the biological performance of the PBR systems at different NH_3 and CO_2 concentration levels (Scenario 1), four parameters were considered. Table 2 provides the criteria involved in the assessment and a description of the performance parameters. The high dry biomass concentration appeared to be the most dominant factor according to the weights and weight system matrix of the biological performance criteria calculated using the CILOS method (Table 3). The second most dominant factor was cell concentration.

Table 3. Criteria weights for all scenarios.

Criteria/Scenario	Scenario 1	Scenario 2	Scenario 3
q_1	0.2687		0.1860
q_2	0.2710		0.2130
q_3	0.2066		0.1347
q_4	0.2537		0.1318
q_5		0.2885	0.0801
q_6		0.1138	0.0504
q_7		0.2880	0.0801
q_8		0.3098	0.1238

S. dimorphus showed the highest normalized cell number (2.21 ± 0.14, $p < 0.01$ compared with other test conditions) with 12 ppm NH_3 and 3500 ppm CO_2 (EXP 14). The maximum specific growth rate of *S. dimorphus* occurred on the second day of the experiment; the highest rate was 0.83 d^{-1} with 25 ppm NH_3 and 3500 ppm CO_2 (EXP15). Dry biomass concentration was significantly higher (1.16 ± 0.08 g L^{-1}, $p < 0.01$) with 25 ppm NH_3 and 2350 ppm CO_2 (EXP 11) than that of other test conditions. The maximum values of performance parameters differed with NH_3 and CO_2 concentrations. The biological performance must stay at the optimum level to reduce the air pollutants released from pig houses. The MCDM method allows one to include different NH_3-CO_2 concentration combinations in a decision-making process and provides an opportunity to simultaneously evaluate multiple biological factors such as cell number, dry weight, cell weight, and maximum growth rate. Optimal CO_2 and NH_3 concentrations for algal growth to reduce air pollutants from animal feeding operations are the most significant factor controlling mitigation efficiencies, and thus directly affect the indoor air quality of barns and environmental pollution.

The experimental conditions that resulted in the best biological performance were those in EXP 14. EXP11 and EXP7 ranked second and third, respectively. The worst-performing experiments were found to be EXP13, EXP9 and EXP5. Table 4 presents the ranking of the sixteen experiments by biological performance, as determined using the GRA method (Equations (7)–(18)).

Table 4. Grey Relational Coefficient Matrix and Ranks for Scenario 1 and 2.

Experiments/Criteria	Scenario 1						Scenario 2					
	Grey Relational Coefficient Matrix				Criteria Weights Differ		Grey Relational Coefficient Matrix				Criteria Weights Differ	
	C_1	C_2	C_3	C_4	Γ_{0i}	Rank	C_5	C_6	C_7	C_8	Γ_{0i}	Rank
EXP1	0.333	0.333	0.429	1.000	0.522	7	0.333	0.333	0.429	1.000	0.567	5
EXP2	0.441	0.424	0.500	0.370	0.431	13	0.441	0.424	0.500	0.370	0.434	12
EXP3	0.470	0.443	0.629	0.522	0.509	8	0.470	0.443	0.629	0.522	0.529	6
EXP4	0.460	0.453	0.506	0.559	0.493	9	0.460	0.453	0.506	0.559	0.503	9
EXP5	0.355	0.351	0.333	0.404	0.362	16	0.355	0.351	0.333	0.404	0.363	16
EXP6	0.660	0.659	0.448	0.375	0.544	5	0.660	0.659	0.448	0.375	0.511	7
EXP7	0.763	0.786	0.650	0.333	0.637	3	0.763	0.786	0.650	0.333	0.600	3
EXP8	0.511	0.513	0.406	0.395	0.460	10	0.511	0.513	0.406	0.395	0.445	11
EXP9	0.380	0.377	0.415	0.463	0.407	15	0.380	0.377	0.415	0.463	0.415	15
EXP10	0.650	0.643	0.443	0.380	0.537	6	0.650	0.643	0.443	0.380	0.506	8
EXP11	0.831	0.931	0.494	0.337	0.663	2	0.831	0.931	0.494	0.337	0.592	4
EXP12	0.484	0.476	0.448	0.350	0.441	12	0.484	0.476	0.448	0.350	0.431	13
EXP13	0.445	0.440	0.429	0.402	0.429	14	0.445	0.440	0.429	0.402	0.426	14
EXP14	1.000	1.000	0.534	0.351	0.739	1	1.000	1.000	0.534	0.351	0.665	1
EXP15	0.562	0.540	1.000	0.441	0.616	4	0.562	0.540	1.000	0.441	0.648	2
EXP16	0.455	0.450	0.549	0.398	0.459	11	0.455	0.450	0.549	0.398	0.464	10

3.2. Environmental Performance

There are many factors affecting environmental performance, such as species-related and environmental influence on CO_2 and NH_3 fixation and the product yield of the microalgae. In the second scenario of the study, the environmental performance of microalgae grown in the PBR system at different NH_3 and CO_2 concentration levels was investigated. The environmental performance parameters were determined as CO_2 fixation, NH_3 fixation, CO_2 removal efficiency, and NH_3 removal efficiency (Table 2). NH_3 removal efficiency appears to be the most dominant factor for the environmental performance, and the second dominant factor was CO_2 fixation. The CILOS method processing steps (Equations (1)–(6)) for the weights and weight system matrix of the environmental performance criteria are shown in Table 3.

S. dimorphus showed the maximum CO_2 fixation (432.24 ± 41.09 mg $L^{-1}d^{-1}$) in EXP 11 (25 ppm NH_3 and 2350 ppm CO_2), while the maximum CO_2 removal efficiency (23.84 ± 2.73%) was achieved in EXP 7 (25 ppm NH_3 and 1200 ppm CO_2). This is because the amount of CO_2 supplied to the system in EXP 7 was 1200 ppm, while the amount of CO_2 supplied in EXP 11 was 2350 ppm. Similar results were observed for the NH_3 fixation and removal efficiencies. While the maximum NH_3 fixation was 23.8 ± 2.26 mg $L^{-1}d^{-1}$ in EXP 11 (25 ppm NH_3 and 2350 ppm CO_2), the maximum NH_3 removal efficiency (100 ± 6.95%) was achieved at 12 ppm NH_3 at all CO_2 concentrations.

The main purpose of reducing the air pollutants released from livestock farms by microalgae is to reduce both NH_3 and CO_2 gases in the barn environment most effectively. However, according to the results of the experiments conducted at 16 different NH_3-CO_2 concentrations, the reduction amounts of ammonia and carbon dioxide gases do not change proportionally in all experiments. For example, the CO_2 and NH_3 removal efficiencies vary independently for different gas concentrations. Ryu et al. [54] reported that *Chlorella* sp. had higher cell concentrations with increased CO_2 concentrations, but CO_2 fixation efficiency was lower at elevated CO_2 concentrations. When the results obtained in the study are analyzed statistically, the results identify the experiments in which the highest values of environmental parameters were obtained independently from each other. However, determining the optimum condition by considering all the environmental parameters together would allow more efficient reduction in the gases released from barns.

According to the results of Scenario 2, the first-ranked experiment was EXP14 which had 12 ppm NH_3 and 3500 ppm CO_2 gas concentrations. This experiment was followed by EXP15, EXP7 and EXP11. The worst-performing experiments were found to be EXP5, EXP8 and EXP13. Table 4 presents the ranking of the 16 experiments in terms of environmental performance, as determined using the GRA method (Equations (7)–(18)).

Aerial pollutants (NH_3 and CO_2) emitted from animal feeding operations affect the air quality of the environment, the neighborhood, and the health of both animals and workers. These air pollutant emissions are currently being regulated by national regulations and international protocols that aim to reduce air pollutant emissions from intensive livestock farming [55]. Reducing air pollutant concentrations to acceptable levels for human and environmental quality is the main objective of every environmental protection agency or regulatory body in developed or developing countries [56]. Microalgae can be used to remove these air pollutants and produce valuable products in bio-mitigation.

3.3. Overall Performance: Selection of the Optimal CO_2 and NH_3 Concentrations

The biological and environmental performance of the PBR system was evaluated in Scenarios 1 and 2, respectively. EXP 14 was ranked first for biological and environmental performance according to the MCDM methods. In the third scenario, the overall performance including all the biological and environmental parameters was investigated. The weights and weight system matrix of the overall performance criteria calculated using the CILOS method processing steps (Equations (1)–(6)) are shown in Table 3. Figure 3 shows the criteria weights for all scenarios.

According to the biological and environmental performance, EXP 14 was ranked one (Figure 4). However, the experiment ranking changed when all performance parameters were analyzed together. EXP11 was identified as the most optimal experiment for overall performance (Figure 4). EXP14 and EXP7 were the second and third ranked, respectively. The worst-performing experiments were found to be EXP13, EXP9 and EXP5. Table 5 presents the ranking of the 16 experiments in terms of overall performance.

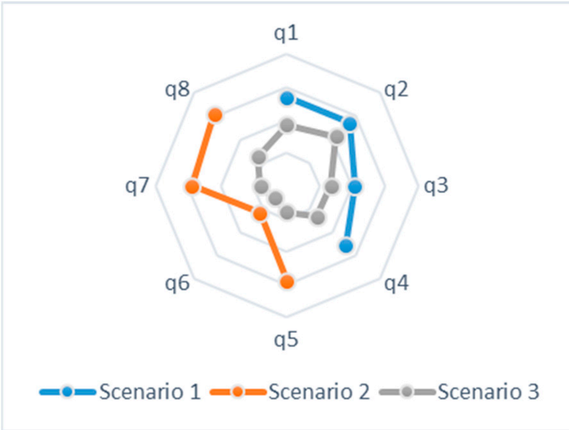

Figure 3. Criteria weights for all scenarios.

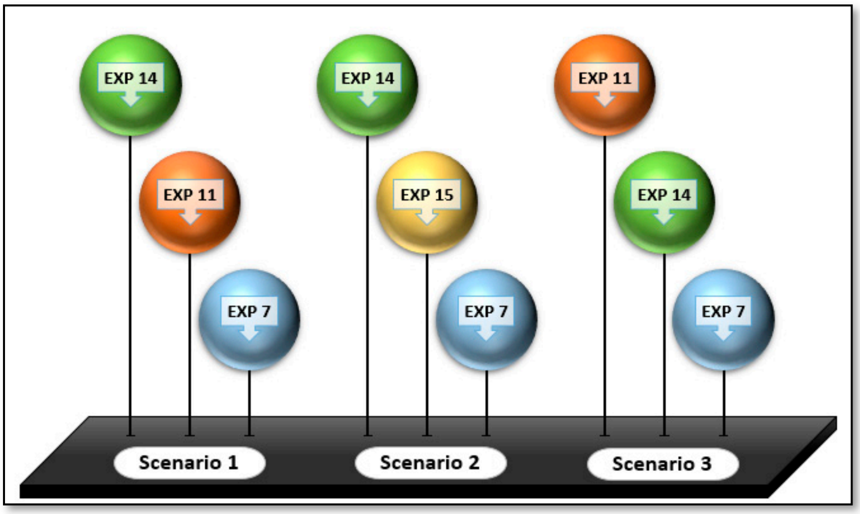

Figure 4. Ranks for all scenarios.

Table 5. Grey Relational Coefficient Matrix and Ranks for Scenario 3.

	Grey Relational Coefficient Matrix								Criteria Weights Differ	
Experiments/Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	Γ_{0i}	**Rank**
EXP1	0.333	0.333	0.429	1.000	0.333	0.333	0.333	0.333	0.434	13
EXP2	0.441	0.424	0.500	0.370	0.394	0.884	0.394	0.681	0.480	8
EXP3	0.470	0.443	0.629	0.522	0.381	0.683	0.381	0.439	0.485	7
EXP4	0.460	0.453	0.506	0.559	0.374	0.600	0.374	0.372	0.460	10
EXP5	0.355	0.351	0.333	0.404	0.333	0.333	0.333	0.333	0.350	16
EXP6	0.660	0.659	0.448	0.375	0.475	0.514	0.475	1.000	0.599	4
EXP7	0.763	0.786	0.650	0.333	0.762	1.000	0.762	1.000	0.737	3
EXP8	0.511	0.513	0.406	0.395	0.416	0.436	0.416	0.411	0.450	11
EXP9	0.380	0.377	0.415	0.463	0.337	0.337	0.337	0.333	0.380	15
EXP10	0.650	0.643	0.443	0.380	0.446	0.393	0.446	1.000	0.583	5
EXP11	0.831	0.931	0.494	0.337	1.000	0.558	1.000	1.000	0.776	1
EXP12	0.484	0.476	0.448	0.350	0.547	0.436	0.547	0.530	0.473	9
EXP13	0.445	0.440	0.429	0.402	0.364	0.345	0.364	0.333	0.404	14
EXP14	1.000	1.000	0.534	0.351	0.567	0.400	0.567	1.000	0.752	2
EXP15	0.562	0.540	1.000	0.441	0.398	0.357	0.398	0.484	0.554	6
EXP16	0.455	0.450	0.549	0.398	0.398	0.357	0.398	0.394	0.438	12

3.4. Sensitivity Analysis

Sensitivity analysis is a procedure performed to test the consistency and measure the power of decision problem results. In this study, sensitivity analysis was performed to test the consistency and measure the power of the results obtained with CILOS and GRA. The results of the third scenario, including all the criteria, and the results of other MCDM methods were compared. For the sensitivity analysis, Weighted Aggregated Sum Product Assessment (WASPAS), Multi-Attribute Ideal-Real Comparative Analysis (MAIRCA), Additive Ratio Assessment (ARAS), Multi-Attributive Border Approximation Area Comparison (MABAC) and The Complex Proportional Assessment (COPRAS) methods were used. The weights used in all methods were those calculated by the CILOS method. The correlations between the methods listed above and the results of the GRA method were tested with Spearman's rho rank correlation. The results are shown in Table 6.

Table 6. Spearman's Rho correlation values between methods.

Method	WASPAS	MAIRCA	ARAS	MABAC	COPRAS
GRA	0.988 *	0.991 *	0.991 *	0.991 *	0.991 *

* A significant data difference methods.

When Spearman's Rho values are examined, excellent correlations are observed between the rankings obtained by all other MCDM methods and the rankings obtained by the GRA method. These results prove that GRA is a consistent method with high-measuring power.

4. Conclusions

This study demonstrated the use of a multi-criteria analysis methodology combined with different CO_2 and NH_3 levels to improve the CO_2 and NH_3 fixation ability of *S. dimorphus*. The MCDM results show that for both the biological and environmental performance, the optimal combination of CO_2 and NH_3 concentrations is 12 ppm NH_3 and 3500 ppm CO_2. However, the optimal CO_2 and NH_3 concentrations for the overall performance were 25 ppm NH_3 and 2350 ppm CO_2. The results of this study allow producers to determine the maximum mitigation of CO_2 and NH_3 concentrations and optimise the operating parameters of PBRs for various housing types, such as dairy, poultry, and pig barns.

For example, in the poultry sector, air pollutants released from poultry houses vary depending on the breeding period of the chickens. While the air pollutant concentrations released from hen houses are low in the first days of the production period, they increase towards the end of production. Meanwhile, engineering options are available to adjust the CO_2 and NH_3 concentrations in the exhaust air from animal barns and the PRB's algal growth. For the exhaust air, the CO_2 and NH_3 concentrations that feed into a PBR can be regulated by changing ventilation/heating configuration or settings, installing pre-scrubbers, and so on. For the algal broth, the concentrations can be adjusted by amending the liquid with carbonate or ammonium salts that are readily available on most farms. Therefore, knowing the gas concentrations at which the most effective CO_2 and NH_3 reductions can be achieved can facilitate the setup and operation of the PBR system. This study indicates that such information can be generated from MCDM analyses. Although still technically intimidating to most producers, the selected MCDM methods are far simpler and require less computing power than artificial intelligence methods (e.g., machine learning). Therefore, they can be translated into Web calculators or MS Excel-based tools that are easily adopted by producers, or implemented in animal barn controllers to automate the facility operation.

Overall, this study presents clear results that can guide decision-makers in choosing the best PBR operating parameters. This MCDM method will aid future algal phytoremediation research for enhancing CO_2 and NH_3 mitigation and minimizing the environmental impacts of animal feeding operations.

In light of the above conclusions, the following tasks are recommended for future research:

- Additional MCDM methods should be explored to broaden the scope of the multi-criteria decision-making process in air pollutant mitigation using PBR systems.
- The significance of the carbohydrate, protein, and fat values of microalgae as criteria should be further investigated. The analysis would facilitate a multi-criteria assessment not only regarding reducing air pollutants emitted from barns but also in evaluating the potential utilization of the obtained biomass in sectors such as animal feed, biodiesel, and others.
- It is advisable to develop an evaluation tool utilizing the MCDM methods examined in this study. Such a tool would simplify the air pollutant mitigation process and facilitate the comparison of the applicability of microalgae in various sectors.

Author Contributions: All authors who meet authorship criteria are listed as authors. Conceptualization, S.U. and T.A.; methodology, S.U. and T.A.; validation, S.U., T.A. and X.Y.; investigation, S.U.; data curation, S.U. and G.A; writing—original draft preparation, S.U. and T.A.; writing—review and editing, S.U., T.A., G.A. and X.Y.; visualization, S.U. and T.A.; supervision, X.Y. and G.A.; funding acquisition, S.U. and X.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by a collaboration between the South Dakota State University Agricultural Experiment Station, Bursa Uludag University, and The Council of Higher Education of Turkey (YUDAB Scholarship). The efforts of Yang were sponsored by the USDA NIFA Hatch (SD00H709-20) and Multistate Hatch Projects (SD00R690-20) through the South Dakota Agricultural Experimental Station.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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