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Research Article

Optimization Strategy for Reducing CO_2 in Livestock Farming with IoT Integration and Decision Support System Approach Using Linear Programming

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Abstract:

Introduction: Livestock waste mismanagement contributes significantly to CO_2 emissions, adversely affecting animal health and environmental sustainability. This study aims to develop an optimization strategy for reducing CO_2 levels in livestock environments through the integration of Internet of Things (IoT) technology and a Decision Support System (DSS) using Linear Programming. **Methods**: IoT sensors were deployed to monitor environmental parameters such as CO_2 levels, temperature, and humidity in real time. A Linear Programming (LP) model was formulated to determine the optimal frequency of two CO_2-reducing actions: spraying Effective Microorganisms (EM4) and performing waste dredging. The objective was to maximize CO_2 reduction under cost and time constraints. The model iteratively updated its parameters based on sensor data feedback, ensuring dynamic and adaptive optimization. **Results**: Simulation results indicated that the LP model successfully identified optimal actions within predefined constraints. The optimal strategy was spraying EM4 eight times over eight days, achieving a CO_2 reduction of 800 ppm with a total cost of Rp 400,000—within the Rp 500,000 budget limit and 8-hour duration constraint. Validation through simulation confirmed the model's accuracy, with prediction deviations consistently falling within an acceptable threshold (±20 ppm). **Conclusions**: The integration of IoT with an LP-based DSS offers a practical and efficient solution for CO_2 reduction in livestock farming. This system enhances decision-making for environmental management, demonstrating potential for scalable application in sustainable agriculture. Future work should incorporate more environmental variables and broader validation to improve model generalizability and precision.

Keywords: Decision Support System, IoT, Linear Programming, Livestock Waste, Optimization of CO_2 Reduction.

1. Introduction

The management of livestock environments poses its own challenges, especially in maintaining air quality that can affect livestock health and environmental sustainability. CO_2 emissions that pollute the atmosphere can disrupt the lives of humans, plants, and animals. The presence of emission gases in the atmosphere shows a significant relationship between environmental pollution and human health [1]. CO_2 emissions from livestock waste are often a cause of declining air quality. Livestock greenhouse gas (GHG) emissions by region show that Asia produces the most, followed by Latin America and the Caribbean, Europe, North America, Africa, and Oceania [2]. Environmental conditions in livestock farming that affect the health and stress levels of livestock include CO_2 levels, humidity, and temperature Therefore, an innovative approach is needed to keep CO_2 levels in livestock farms below the permissible CO_2 threshold [3], [4].

Internet of Things (IoT) technology has opened new opportunities for real-time monitoring of livestock environments, especially CO_2 levels, humidity, and temperature conditions through continuous IoT sensors to support decision-making [5]–[8]. These factors are considered because livestock stress levels, among others, depend on temperature and humidity. The impact of heat stress on livestock can be categorized into feed nutrient

use, feed intake, livestock production, reproduction, health, and death. In addition, integration with the Decision Support System (DSS) [9], [10] approach enables optimization in determining the frequency of spraying Effective Microorganisms (EM4) solution or waste dredging to optimize CO_2 reduction [11]–[14]. Composting can be an effective method for reducing greenhouse gas (GHG) emissions from various waste materials, including animal manure.

Theoretically, this research adds to the literature on the application of the Internet of Things (IoT) in the efficiency of livestock environment management by optimizing CO_2 reduction in livestock farms. Additionally, by developing a Linear Programming-based Decision Support System (DSS) model, it can support more efficient CO_2 reduction optimization by utilizing real-time data from IoT sensors. This approach is also based on previous studies that applied quantitative methods in decision support systems. For instance, the stud the study "Community Decision Support Service System Village Level Mandiri Based On An Interactive Website" [15] utilized a web-based system to support community decision-making based on real-time information.

This research adopts similar principles by applying Linear Programming (LP) in Decision Support Systems (DSS) to determine optimal strategies for IoT-based livestock waste management [16]–[19]. By combining real-time monitoring through sensors with an LP-based optimization model, this system can provide more precise and efficient action recommendations compared to conventional methods [20], [21]. The practical contribution of this research is the development of a model that determines the optimal strategy between spraying Effective Microorganisms (EM4) solution and waste dredging. This model can help provide solutions for more efficient organic waste management to optimize CO_2 reduction, thereby creating a healthier environment for livestock and their surroundings.

2. Method:

This research uses a quantitative approach with an experimental design to test the effectiveness of integrating IoT technology and Linear Programming (LP)-based DSS in optimizing CO_2 reduction [22], [23]. The objective function of this LP method is to maximize the reduction of CO_2 concentration (ppm). The LP model is used to determine the optimal actions based on cost and time constraints, with the objective function of maximizing CO_2 reduction through two methods: spraying and waste dredging. Here is the flowchart that illustrates the optimization process based on IoT and Linear Programming (LP) for decision-making in environmental management [24]–[26]. The sequence begins with sensor data collection, processing with the LP model, result verification, and corrective actions if the results are not optimal. Once the actions are implemented, new data is collected for continuous improvement.

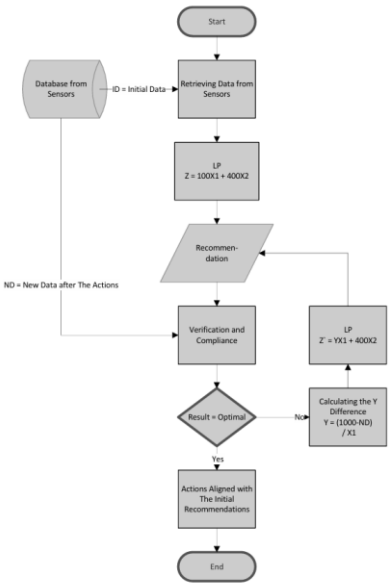


Figure 1. Flowchart of the optimization process based on IoT and LP-based DSS for livestock waste management

Formulation of the Linear Programming Model

The objective function is to optimize CO_2 reduction.

$$Z = 100X1 + 400X2$$

Where: $X1$ = is the frequency of spraying

$X2$ = is the frequency of dredging

Constraints:

1) $50.000\ X_1 + 300.000\ X_2 \leq 500.000$ (Cost Constraints)
2) $1\ X_1 + 5\ X_2 \leq 8$ (Duration Constraints)
3) $X_1 \geq 0; X_2 \geq 0$ (Non-Negativity Constraints)

The following are the process flow steps for the integration of IoT and LP-based DSS:

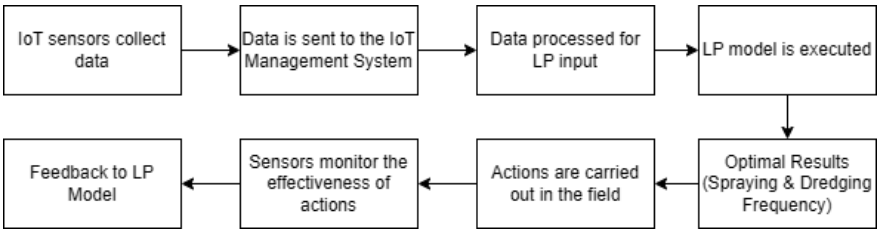


Figure 2. Flow of IoT Sensor Integration and LP Model for Optimizing Spraying & Dredging Frequency

a. Initial Data Collection from IoT
   IoT sensors measure data such as CO_2 levels, humidity, and ambient temperature. This data is transmitted to a central system for processing.
b. Input Data into the LP Model
   Based on the received CO_2 data, the system processes the LP model to determine the optimal action. For example, the LP results might suggest spraying 8 times to achieve a CO_2 reduction target of 800 ppm.
c. Action Implementation
   The spraying is carried out 8 times in the field as recommended by the LP model. During each spraying session, CO_2 levels are monitored to assess the effectiveness of the action.
d. Effectiveness Measurement of Actions
   After the actions are completed, IoT monitors CO_2 levels again to ensure the target (800 ppm) is achieved. The possible outcomes are as follows:
   Achieved: If the CO_2 reduction target is met (800 ppm from 8 sprays), the formula Z=100x1+400x2 can be used without changes in the next iteration.
   Not Achieved: If the CO_2 reduction is below the target, the data is reanalyzed.
e. Adjustment of Action Efficiency
   If the average reduction per spray turns out to be greater or smaller than the initial estimate (100 ppm per spray), this data is used to update the parameters for improved accuracy:
   For example, if the reduction from 8 sprays is only 600 ppm, the average reduction per spray would be 75 ppm instead of 100 ppm. The LP formula is then updated based on the actual data:
   New Formula: Z = 75x1 + 400x2, where x1 is adjusted to reflect the actual results.
f. Continuous Iteration
   Data from the actions performed is sent to the system for evaluation. The LP model recalculates using the new data to determine the next optimal actions. This process is carried out continuously every month or according to the planned evaluation cycle.
g. System Validation and Improvement
   The system periodically performs validation to ensure that the formulas and LP parameters remain relevant to actual field conditions. If significant discrepancies are found between actual results and predictions, the LP parameters are updated and dynamically adjusted based on IoT data.

Linear Programming Modeling

The objective function with this LP method is to optimize the value of CO_2 concentration reduction (ppm). Actions to reduce CO_2 concentration (ppm) values are through spraying and dredging. Each time spraying costs Rp 50,000 and takes 1 hour, whereas each time dredging costs Rp 300,000 and takes 5 hours to complete. The constraints for the action cost are Rp 500,000 and for the duration are 8 hours.

Each time spraying can reduce CO_2 concentration by 100 ppm, whereas each time dredging can reduce CO_2 concentration by 400 ppm.

Objective Function:

$$Z = 100X1 + 400X2$$

Where:
$X1$ = is the frequency of spraying
$X2$ = is the frequency of dredging
Z = Total CO_2 Reduction

Constraint Function:

- $50.000\ X_1 + 300.000\ X_2 \leq 500.000$ (Cost Constraints)
- $1\ X_1 + 5\ X_2 \leq 8$ (Duration Constraints)
- $X_1 \geq 0; X_2 \geq 0$ (Non-Negativity Constraints)

Illustrate All Constraints to Determine the Feasible Solution Space

1) Cost Contains

The equation $\mathbf{50,000\ X_1 + 300,000\ X_2 \leq 500,000}$ can be transformed into the equation:

$\mathbf{50,000\ X_1 + 300,000\ X_2 = 500,000}$.

To make it easier to draw constraint lines, determine two opposite points.

From the equation: $\mathbf{50,000\ X_1 + 300,000\ X_2 = 500,000}$

If $\mathbf{X_1 = 0 \rightarrow 50.000\ (0) + 300.000\ X_2 = 500.000}$

$$\mathbf{0 + 300.000\ X_2 = 500.000 \rightarrow X_2 = 500.000/300.000 = 1,67}$$

If $\mathbf{X_2 = 0 \rightarrow 50.000\ X_1 + 300.000\ (0) = 500.000}$

$$\mathbf{50.000\ X_1 + 0 = 500.000 \rightarrow X_1 = 500.000/50.000 = 10}$$

The Drawing of the Objective Function Line from the Cost Constraints:

$$\mathrm{X} \rightarrow \mathbf{50.000X_1 + 300.000X_2 = 500.000}$$

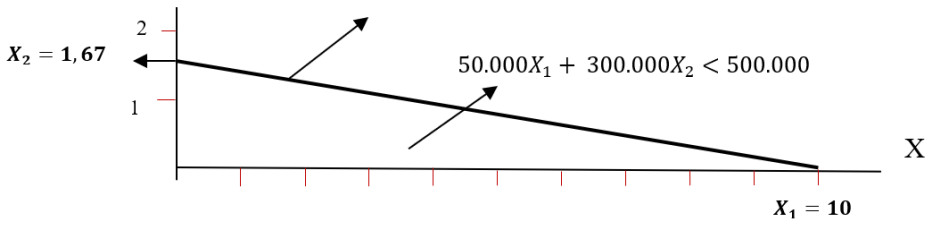


Figure 3. Objective Function Line for Cost Constraint

2) Duration Contains

The equation $1X1 + 5X2 \leq 8$ can be transformed into the equation: $1X_1 + 5X_2 = 8$
To make it easier to draw constraint lines, determine two opposite points.
From the equation: $1X_1 + 5X_2 = 8$
If $X_1 = 0 \rightarrow 1X_1 + 5X_2 = 8$

$$0 + 5X_2 = 8 \rightarrow X_2 = \frac{8}{5} = 1,60$$

If $X_2 = 0 \rightarrow 1X_1 + 5X_2 = 8$

$1X_1 + 5\,(0) = 8 \rightarrow X_1 = \frac{8}{1} = 8$

The Drawing of the Objective Function Line from the Duration Constraints:

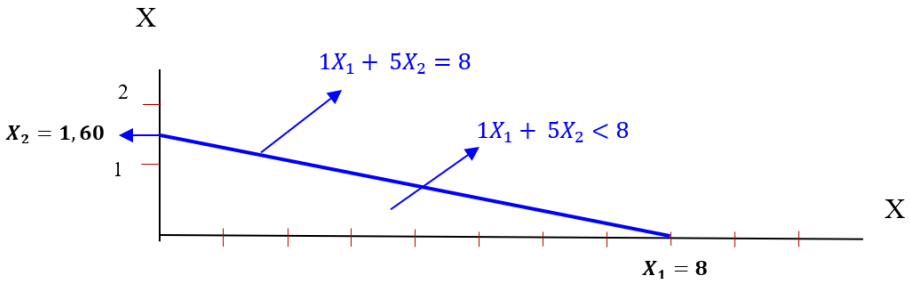


Figure 4. Objective Function Line for Time Constraint

3) The feasible set area is the area encompassed by the cost and duration constraints, which includes point A, B, and C.

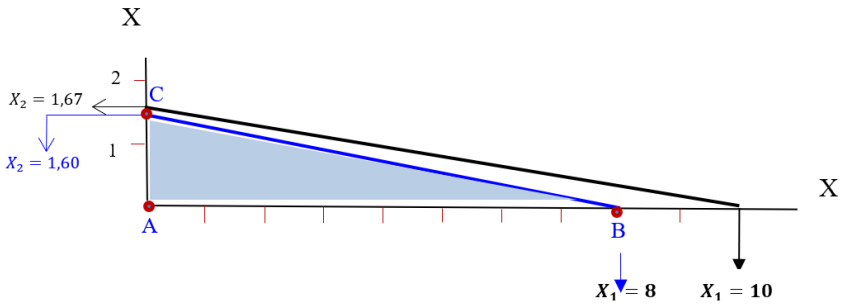


Figure 5. Feasible Set Area

Finding the Value of Z from Each Extreme Point

The feasible area includes area ABC

a. Point A:

Coordinates of Point A (0;0) → X1 = 0; $X_2 = 0$
Maximization Z = $100X1 + 400X_2$
100 (0) + 400 (0) = 0

b. Point B:

Coordinates of Point B (8;0) → X1 = 8; $X_2 = 0$
Maximization Z = $100X1 + 400X_2$
100 (8) + 400 (0) = 800

c. Point C:

Coordinates of Point C (0;1,60) → X1 = 0; $X_2 = 1,60$
Maximization Z = 100 (0) + 400 (1,60)
0 + 640 = 640

Obtaining the Optimal Solution

Table 1. Solution Results Table

Extreme Points	Spraying Frequency (X1)	Dredging Frequency (X2)	Efficient CO_2 Reduction Optimization Max Z = $100X1 + 400X_2$
A	0	0	0
B	8	0	800
C	0	1,60	640

Based on calculations from the Linear Programming model, spraying 8 times can reduce CO_2 emissions by 800 ppm. With an operational cost of 400,000 rupiah, this cost remains within the allocated budget.

This solution demonstrates the optimal allocation of resources in determining actions and frequencies needed to maximize CO_2 reduction (800 ppm). Spraying appears to be more suitable for short-term use under the given constraints, providing an efficient and practical approach within budget and time limitations.

Validation with Simulation Data

Validation of LP Model When Recommendations Align with CO_2 Emission Reduction Targets

Definition of Validation:

- CO_2 Reduction Target (8 Days): 800 ppm
- LP Prediction: 100 ppm per spray (Z=100X1Z = 100X_1Z=100X1)
- Validation Threshold: The acceptable range of deviation is within (-20) to 20 ppm from the target.
- Validation Condition: The Linear Programming model is considered valid if the actual CO_2 reduction falls within the range of 780 ppm to 820 ppm.

Calculate the Difference Between Actual and Target.

Table 2. Spraying Actions Table

Day	Spraying Frequency (X1)	Prediction of CO_2 Reduction (LP) (Z=100X1)	Actual CO_2 Reduction	Difference (Prediction - Actual)	Validation (✔ if within -20 to 20)
1	1	100	80	**20**	✔ Valid
2	1	100	90	**10**	✔ Valid
3	1	100	95	**5**	✔ Valid
4	1	100	95	**5**	✔ Valid
5	1	100	90	**10**	✔ Valid
6	1	100	100	**0**	✔ Valid
7	1	100	100	**0**	✔ Valid
8	1	100	110	**-10**	✔ Valid

Validation Analysis

- ✓ All days meet the validation criteria.
- ✓ The difference between the LP prediction and the actual results remains within the safe range (-20 to 20 ppm).
- ✓ The initial LP model is deemed valid without requiring revision.

Validation of the LP Model by determining the LP improvement method if the recommended actions do not align with the target results

When the CO_2 emission reduction does not meet the target, recommendations for improved LP methods are provided to suggest better actions. Here is the simulation data for the LP recommendations:

The initial CO_2 level is 1000 ppm (the maximum threshold). After applying the LP method, but failing to meet the target CO_2 emission reduction, recommendations for improved LP methods are created to align with the results of the actual CO_2 reduction.

Table 3. Simulation of Adjusted LP Based on CO_2 Reduction After Recommended Actions

Case	Spraying Frequency (X1)	Dredging Frequency (X2)	CO_2 Reduction in the LP Model (ppm)	Actual CO_2 Reduction (ppm)	Y Difference	New LP
1	8	0	800	600	1000 - 600 = 400	$Z' = 75X1 + 400X2$

Case	Spraying Frequency (X1)	Dredging Frequency (X2)	CO_2 Reduction in the LP Model (ppm)	Actual CO_2 Reduction (ppm)	Y Difference	New LP
2	6	1	700	650	1000 - 650 = 350	$Z' = 87,5X1 + 400X2$
3	4	2	600	500	1000 - 500 = 500	$Z' = 100X1 + 400X2$

Because there has been no prior research directly linking IoT and LP to optimize CO_2 reduction in farming, this study provides a novel contribution to the field. Additionally, further testing is required to confirm its reliability under various conditions. The developed model still needs to be validated with real-world data to ensure its applicability on a larger scale or in diverse environmental settings.

This optimization system modeling, based on Linear Programming (LP), integrates real-time input data from IoT devices into the system. The system then performs LP calculations to determine (X_1) (spraying frequency) and (X_2) (dredging frequency) optimally. The system can be designed to update results whenever there are changes in field conditions

3. Results and Discussion

The simulation results indicate that this method can optimally allocate resources while considering cost and time constraints. Spraying 8 times over 8 days successfully reduces CO_2 levels by 800 ppm, with the total cost remaining within the specified budget limits. Based on the results of the Linear Programming calculations, spraying 8 times meets all the cost and duration constraints. Dredging is not required because it costs too much to meet the same constraints. The total cost incurred is Rp400,000, which is below the limit of Rp500,000, with a total usage time of 8 hours, which is within the maximum limit. The solution shows the best resource allocation in determining actions and the required frequency to maximize CO_2 reduction (800 ppm). Spraying is more suitable for short-term use under such constraint conditions.

4. Conclusion

The installed IoT (Internet of Things) technology is used to monitor CO_2 levels, humidity, and temperature in real-time, with the data being automatically integrated into the data management system through the IoT Gateway. This research contributes to the efficiency of livestock environmental management by integrating Internet of Things (IoT) technology and Linear Programming (LP) methods to optimize CO_2 emission reduction. The IoT-LP concept applied in this study offers an innovative solution for reducing greenhouse gas emissions on farms, while simultaneously supporting more sustainable and efficient livestock practices. The model can also assist farm owners in making data-driven decisions to control air quality more effectively

The use of IoT technology in this research is still at a basic stage, so further development is highly recommended to integrate more environmental parameters. The hope is that these findings can become one of the alternatives for optimizing CO_2 reduction in livestock farming while aligning with the general principles of resource optimization and the use of IoT technology that has proven successful in other sectors, such as smart agriculture and industrial management.

In future research, real data from different livestock environments and a larger number of livestock can be used. This is to ensure that the developed optimization model can indeed be applied to real situations. Additionally, the next research can add more environmental parameters such as ammonia (NH_3) levels or other relevant parameters. Recommendations for future research related to IoT technology include implementing more diverse and accurate IoT sensors, and potentially developing the use of big data technology to analyze patterns of CO_2 emission changes over time. With more comprehensive follow-up research, this model has the potential to become a new standard in livestock environmental management, helping to reduce environmental impacts while improving operational efficiency and farm sustainability.

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