Design and Optimization of a Bio-Composter System Using Genetic Algorithm

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ABSTRACT

The Philippine agricultural sector's reliance on costly imported chemical fertilizers creates economic burdens and compromises long-term sustainability. To address this, organic composting provides a local, eco-friendly alternative, but its success relies on achieving consistent, high-quality compost. This study aimed to design and construct a small-scale composter system that utilizes Genetic Algorithm in the quality optimization of composter operational parameters and integrate monitoring and remote capabilities. The study specifically aimed to develop an optimization model using a genetic algorithm to a) to determine the best composter operational parameters for each compost material (soy pulp, vegetable peelings, coffee grounds) and b) to maximize composting efficiency, minimize resource usage and enhance overall sustainability of the system. The resulting NPK values of each compost material were compared to the commercialized fertilizer. The genetic algorithm achieved realistic results in determining the best composter operational parameters for each compost material with the given target NPK(Nitrogen, Phosphorus, Potassium) values. Findings demonstrated that increased runtime significantly improves compost quality, while optimal rotation speed yields diminishing returns beyond a certain threshold. Composter system software also provided ease of use through an interface for composter control and monitoring systems. To further improve the system, integration of advanced automation and upgrading the motor power capabilities are recommended.

Keywords: *Genetic Algorithm, Composter, Fertilizer, NPK, Optimization*

INTRODUCTION

The agricultural sector's reliance on chemical fertilizers to boost crop yields is evident in the Philippines, with 2018 sales hitting 1.2 million metric tons(Authority, 2020). However, local farmers often underutilize nitrogen due to high fertilizer costs, caused by the decline in domestic production(David & Inocencio, 2019). This cost barrier, combined with limited irrigation access, reduces fertilizer efficiency and crop yields. To address these issues, the Philippine government promotes organic composting via the Composting Facilities for Biodegradable Waste (CFBW) program. However, the quality monitoring of compost remains a challenge.

The prohibitive cost of fertilizers has been identified as a significant barrier, leading to reduced application rates that fall below the levels necessary for optimal crop production (Crisostomo, 2018). Additionally, limited access to irrigation further exacerbates the challenge, restricting the effective use of fertilizers (Agriculture, 2020). These factors contribute to inefficiencies in fertilizer management, which, if addressed, could potentially increase rice yields significantly ((IRRI), 2021).

In response to these challenges, the Philippine government, through the Bureau of Soils and Water Management (BSWM), has promoted the use of organic composting as an alternative to chemical fertilizers. Initiatives such as the distribution of Rotary Composters and Shredder Machines under the Composting Facilities for Biodegradable Waste (CFBW) program aim to enhance organic waste management ((BSWM), 2021). However, these initiatives often lack advanced systems for monitoring the quality of compost produced, which is crucial for ensuring the effectiveness of compost as a fertilizer alternative.

LITERATURE REVIEW

Recent discussions in environmental science underscore the critical balance required in nitrogen fertilization, highlighting the detrimental effects of overfertilization on both soil health and the environment. Grell (2021) advocates for the development of multi-sensor integrated bio-waste composter systems that utilize machine learning to assess compost quality against commercial fertilizers, pointing out the need for precise nutrient management.

Kim et al. (2018) further emphasizes the role of IoT-enabled remote sensors in monitoring soil nutrients, such as nitrogen. These technologies enable dynamic adjustments based on continuous data streams, which are crucial for maintaining optimal soil health (Grell, et al., 2021).

Focusing on the technical advancements in composting, recent studies have integrated genetic algorithms to enhance composting outcomes. For instance, a significant study by Guochao Ding et al. (2023) utilized a CGA-BP neural network-based model to optimize the aeration oxygen supply in aerobic composting. This model significantly improved the compost's maturity by optimizing oxygen levels, demonstrating the efficacy of combining genetic algorithms with neural networks to refine composting processes (Guochao Ding, 2023).

In another innovative approach, a study involved the use of genetic algorithms to optimize humic acid content in GLR composting (Chun-Fang Shi, 2022). By adjusting various composting parameters, this study highlighted the potential of genetic algorithms in enhancing specific nutrient profiles within composts, underscoring their versatility in environmental management applications.

This study focuses on developing a biowaste composter system using genetic algorithms and sensor technology to improve compost quality. Recent advancements, such as multi-sensor integration and IoT-enabled remote sensors, are being employed to monitor soil nutrients and optimize compost production. Integrating machine learning and genetic algorithms has shown promise in improving composting processes, nutrient profiles, and sustainability in agricultural practices.

METHODS

Materials: Devices, Technologies, and Equipment

1. **Arduino Mega 2560** – The Arduino Mega 2560 is a microcontroller board based on the ATmega2560 chip.Its primary role within our system involves managing electronic components, interfacing with sensors for additional parameter monitoring, and executing programmed tasks essential for optimizing the composting process using genetic algorithms.
2. **Raspberry Pi 4 Model B** – A single-board computer designed for diverse applications, this device supports program execution and data processing which is crucial for implementing genetic algorithms in bio-composting.
3. **Stepper Motor Driver TB6600** – is a driver specifically designed to control stepper motors. A stepper motor is a type of electric motor that rotates in discrete steps. The TB6600 driver serves as a vital link between our system's microcontroller, such as an Arduino, and the stepper motor, enabling accurate and controlled movement essential for optimizing composting processes.
4. **Stepper Motor Nema 23 30kg-cm** – is a standardized stepper motor with a flange diameter of around 2.3 inches and a holding torque of 30 kilogram-centimeters. This specific motor is selected for its ability to provide precise positioning and sufficient torque output, crucial for the operational requirements of the bio-composter system.
5. **Temperature and Humidity Sensor** – The sensor employed in our bio-composter system offers accurate temperature and humidity measurements with rapid response times, high reliability, and resistance to interference.
6. **Hall Effect Sensor –** Integrated circuits that transduce magnetic fields to electrical signals with accuracy, consistency, and reliability. It is a feature for the rotating composter to precisely align the docking system, to ensure convenient and seamless extraction and insertion of compost.
7. **Rotary Composter bin** – a specialized container engineered to optimize the decomposition of organic materials into nutrient-rich compost.
8. **12V Power Supply** – a device that converts mains AC (Alternating Current) electricity from a wall outlet into a stable DC (Direct Current) voltage level.
9. **NPK Testing Kit** – is a soil testing tool measuring levels of Nitrogen (N), Phosphorus (P), and Potassium (K). By analyzing these nutrient levels, the NPK Testing Kit helps optimize fertilization strategies, a vital aspect of our bio-composter system aimed at enhancing the efficiency and productivity of organic waste decomposition through intelligent nutrient management.
10. **Jupyter Notebook** – is an essential open-source web application utilized within our project for interactive data exploration, visualization, model development, and the deployment of genetic algorithms. It serves as a critical tool for processing the data

acquired by our bio-composter system, facilitating efficient model development and analysis.

Design Framework of the Bio-Composter System

The researchers utilize a pre-assembled composter system as the foundational framework for their experimentation. The pre-built composter system functions as the foundation upon which further parts are easily added to improve efficiency and usefulness. The addition of a stepper motor and the device driver is one such modification. The connection between the stepper motor driver and the Arduino Mega board facilitates the comprehensive control of the composter's rotational dynamics, including both its overall rotation and the specific revolutions per minute (RPM) at which it operates.

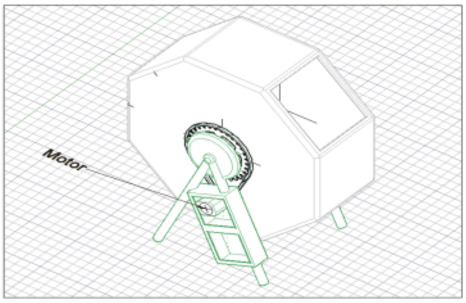

Figure 1. *Rotary Composter Bin Design*

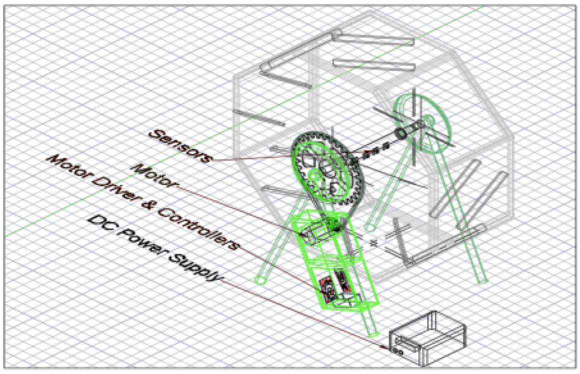

Figure 2. *Overall view of Rotary Composter Bin*

The system is integrated with sensors to monitor the temperature, humidity, Carbon Monoxide content, Hydrogen content, and Ammonia Content. The sensors are then interfaced with Arduino. The serial monitor of the Arduino is then interfaced with the Raspberry Pi to display the values generated from the sensors.

The integration of a Hall effect sensor also adds another layer of precision and convenience to the composting process. It makes the composter dock positioned for extraction and insertion of the compost. That prepares the user to extract or insert compost material efficiently.

Software and Hardware Interfacing of the Bio-Composter System

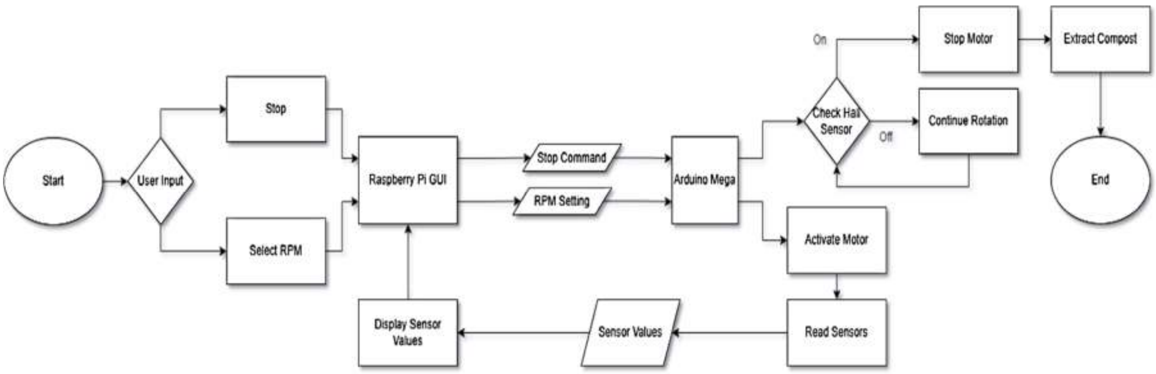

Figure 3. *Bio-Composter System Flow Chart*

The process initiates when the user selects an input through the GUI interface. If the user selects an RPM, this command will be transmitted to the Arduino Mega which initiates the motor. Upon activation, the sensor transmits the values through the Arduino Mega to the GUI interface. Should the user opt to halt rotation, the sensor verifies the Hall Sensor and halts the motor accordingly.

GUI Design and Remote Functionality of the Bio-Composter System

The GUI shows a selection of 3 RPM settings: 4, 6, and 8 RPM. Once the motor activates, the timer will start as well. The timer will not rest until the stop motor command is initiated. Thus, even if the user adjusts the RPM setting during the composting process, the timer will not be reset. The sensor values for the Carbon Monoxide, Hydrogen, Ammonia, Temperature, and Humidity are also displayed in the interface.

Additionally, to make full use of the Raspberry Pi 4, a remote function is added as a feature. This will enable the user to access the GUI interface which makes the composter control and monitoring system accessible from anywhere in the world if there is an internet connection.

Data Gathering

Twenty-seven (27) samples of compost were produced which had varying properties for operational parameters and materials. The parameters varied with the composter are the RPM and the total runtime of the composter rotation. Altering the RPM refers to the speed at which the compost materials are mixed and aerated, which is essential for the microbial activity that breaks down organic matter. The variable RPM settings for the composter are 4, 6, and 8 RPM. The total runtime refers to how long the compost is subjected to the composter for rotation. 1, 2, and 3 hours are the runtime variables used in this study.

For the compost materials—soy pulp, vegetable peelings, and coffee grounds—the composition ratio varies across different samples. For each sample, one compost material is used with a different RPM and runtime variable. 27 combinations are made with each material, RPM, and runtime which makes up the 27 samples for the dataset. After extraction, each compost sample undergoes analysis using an NPK Testing Kit. The validity of this kit is confirmed by comparing its results for two baseline samples with those obtained from comprehensive laboratory NPK measurements. Furthermore, the researchers incorporated assigned values for the Low, Medium, and High indicators of the chart; 3 for Low, 6 for Medium, and 9 for High. Middle values between the indicators were also assigned for more data diversity.

Development of the Genetic Algorithm Models

a. Data Source and Preprocessing

The study utilized a dataset compiled from various composting trials conducted by the researchers. This dataset includes the operational parameters: Rotations Per Minute (RPM), Total Runtime; and the types of materials used (Vegetable Peelings, Soy Pulp, Coffee Grounds). The dataset also includes the resulting NPK (Nitrogen, Phosphorus, Potassium) values for each trial.

b. Parameter Specification

The parameters and their respective ranges were specified as follows, allowing the genetic algorithm to manipulate these within defined limits:

- RPM: 4, 6, 8
- Total Runtime: 1, 2, 3, 4, 5 hours

The target for optimization was set to achieve NPK values of 9, 9, 9.

c. Genetic Algorithm Configuration

Each material type will have a respective genetic algorithm model to determine the best operational parameters for each material.

Each of the genetic algorithms is configured with the following components:

i. *Fitness Function:*

The fitness is calculated based on the Euclidean distance from the target NPK values, employing a squared error penalty to intensify the impact of larger deviations:

$$Fitness = \frac{1}{1 + penalty}, \quad where\ penalty = \sum_{i=1}^{3} \left(NPK_{individual,i} - NPK_{target}\right)^2$$

Figure 4. Fitness Function Computation

ii. *Population Initialization:*

An initial population of 50 individuals was generated, with half derived from the existing dataset of each respective compost material to ensure a realistic starting point, and half randomly generated based on the defined parameter ranges to introduce diversity. This approach is designed to enhance the algorithm's performance, compensating for the limitations of data acquired from testing kits with restricted trial counts. By simulating potential genetic variations, the algorithm expands the dataset, creating scenarios that mimic realistic genetic configurations without the need for additional real-world testing.

iii. *Selection Mechanism:*

Tournament selection was employed with a tournament size of 5, selecting the best out of a randomly chosen subset of the population to proceed to reproduction.

iv. *Crossover and Mutation:*

- Crossover: A two-point crossover method was used, where two random crossover points are selected, and the segments between these points are swapped between two parent individuals to create two offspring.

- Mutation: An adaptive mutation rate starting at 5% was applied, where individual parameters of the offspring were randomly altered within their specific ranges. The mutation rate was increased by 5% every 10 generations if no improvement in fitness was observed.

d. Algorithm Execution

Each of the genetic algorithms ran for 100 generations, with each generation consisting of the selection, crossover, and mutation processes to create a new population. The best individual from each generation was tracked, and its fitness was compared to that of the best individuals from previous generations.

e. Genetic Algorithms Output

Upon completion of the genetic algorithms, the optimized operational parameters of the best individual for each compost material were output along with its respective fitness score. These individuals represented the optimal set of composting parameters that were most likely to achieve the target NPK values according to the model for each respective compost material.

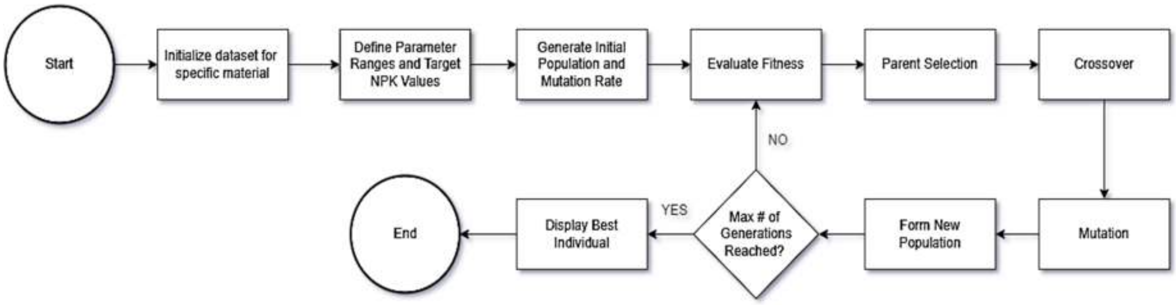

Figure 5. *Genetic Algorithms Flowchart*

RESULTS AND DISCUSSION

Data Gathering Results

1. **Coffee Grounds**

Figure 6. *Coffee Grounds Nitrogen Results*

The x-axis represents the composter runtime values of 1-3 hours, and the y-axis shows the resulting Nitrogen values of the compost upon being tested in the NPK testing Kit. Results show that using coffee grounds as compost and running it at 6 Revolutions Per Minute for 3 hours results in high Nitrogen values which is the desirable amount for the target compost.

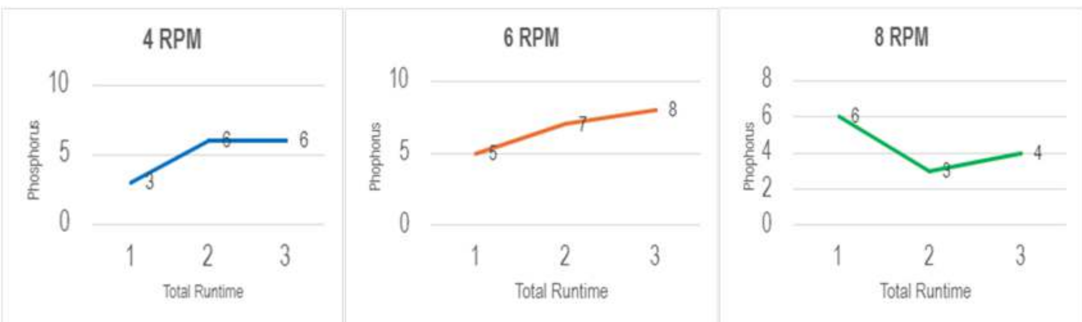

Figure 7. *Coffee Grounds Phosphorus Results*

Phosphorus values reach the desirable Phosphorus value of 8 when composting it at 6 rpm for three hours.

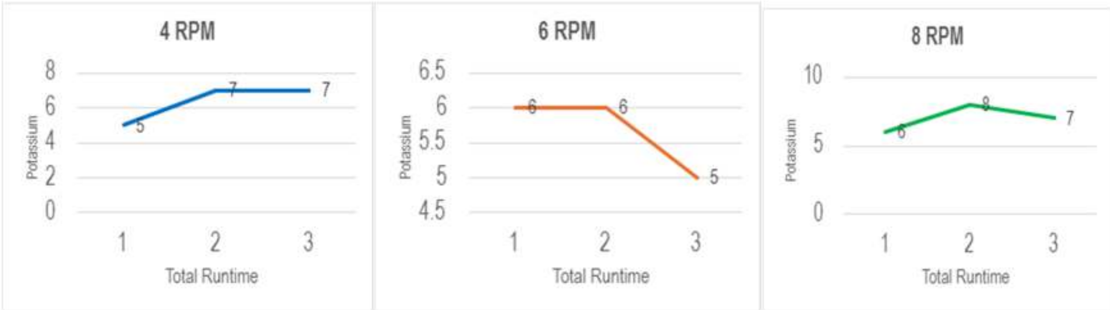

Figure 8. *Coffee Grounds Potassium Results*

The data shows that the target value of Potassium was reached by running the composter for 2 hours on 8 rpm.

2. Soy Pulp

Figure 9. *Soy Pulp Nitrogen Results*

The x-axis represents the composter runtime values of 1-3 hours, and the y-axis shows the resulting Nitrogen values of the compost upon being tested in the NPK testing Kit. Results show that by using soy pulp, the highest value of nitrogen of 7 was achieved when the composter was run for 3 hours at 4 rpm.

Figure 10*. Soy Pulp Phosphorus Result*

The experimentation shows that the optimal value of 8 was achieved by composting the soy pulp in 8 RPM for 2 hours.

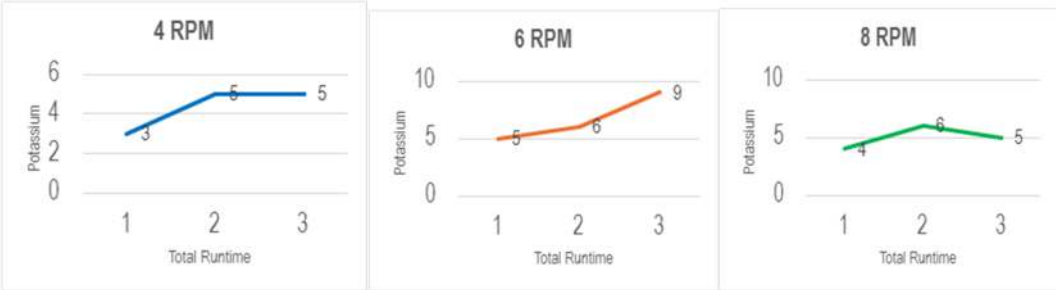

Figure 11. *Soy Pulp Potassium Results*

The graph shows that the target value of 9 was reached when the soy pulp is composted with 6 rpm and an active run time of 3 hours.

3. Vegetable Peelings

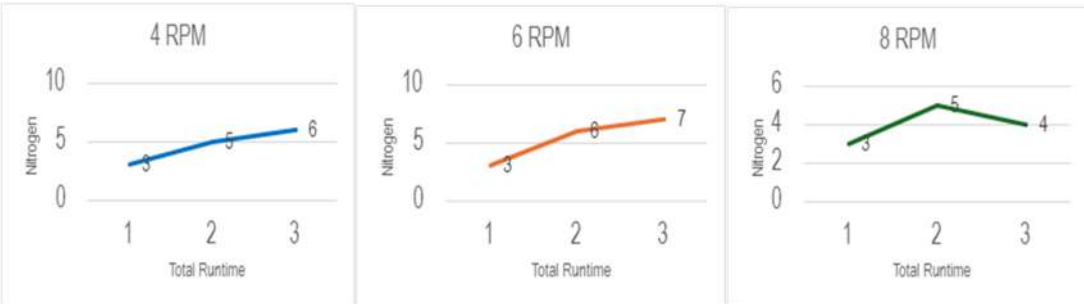

Figure 12. *Vegetable Peeling Nitrogen Results*

Results show that a nitrogen value of 7 was reached given that the composter is running at 6 Revolutions Per Minute for 3 hours.

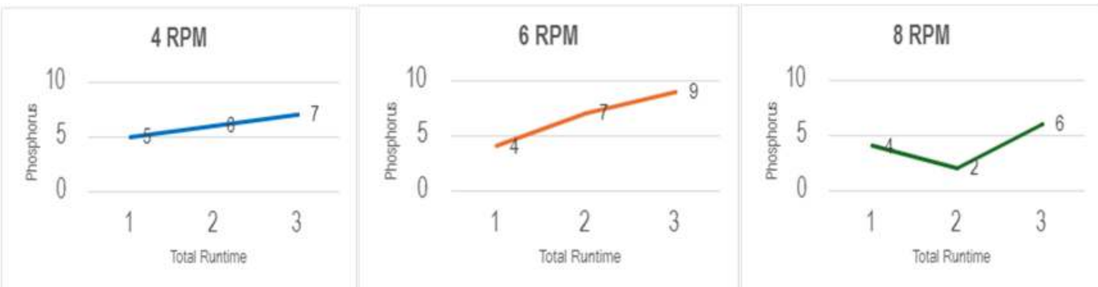

Figure 13. *Vegetable Peelings Phosphorus Results*

The graphs show that a value of 9 for potassium is achieved given that the composter is running at 6 rpm for 3 hours.

Figure 14. *Vegetable Peelings Potassium Results*

The graph shows that a value of 7 for potassium is achieved given that the composter is running at 8 rpm for 2 hours.

b. Genetic Algorithm Models Fitness Testing

1. **Coffee Grounds**

Table 1

Genetic Algorithm Results of NPK using Coffee Grounds with Best Individual Results.

Target Values	Best Individual Parameters
Nitrogen: 9	**RPM: 6**
Potassium: 7	**Total_Runtime: 3.0 hours**
Phosphorus: 8	**Coffee_Grounds: 1.0**
Fitness: 0.1667	

The table shows the best runtime and RPM results for the coffee ground material. Nitrogen shows the highest value, reaching the desired target of 9, followed by Phosphorus with a value of 8, and Potassium with 7. This result correlates with the dataset as coffee grounds have high values for Nitrogen. However, the resulting compost parameters are already indicated in the dataset. Additionally, the resulting NPK values from the dataset are not far off from the NPK values of the genetic algorithm.

2. **Soy Pulp**

Table 2

Genetic Algorithm Results of NPK using Soy Pulp with Best Individual Results.

Target Values	Best Individual Parameters
Nitrogen: 8	**RPM: 8.0**

Potassium: 9	**Total Runtime: 4.0 hours**
Phosphorus: 8	**Soy Pulp: 1.0**
Fitness: 0.3333	

Results for the soy pulp show that Potassium has the highest value, followed by Nitrogen and Phosphorus having the same values. The best runtime and RPM for the composter are 8 and 4 hours, respectively. The resulting runtime hours is 4 due to the adjustment of the parameter ranges for the genetic algorithm, which includes 4 and 5 hours. Soy pulp has a higher fitness score than coffee grounds.

3. **Vegetable Peelings**

Table 3

Genetic Algorithm Results of NPK using Vegetable Peelings with Best Individual Results.

Target Values	Best Individual Parameters
Nitrogen: 9	**RPM: 6.0**
Potassium: 9	**Total_Runtime: 5.0 hours**
Phosphorus: 8	**Vegetable_Peelings: 1.0**
Fitness: 0.5	

NPK Results for the Vegetable peelings show the highest fitness score. 9, 9, and 8 for Nitrogen, Potassium, and Phosphorus, respectively. Optimal compost parameters are 6 RPM and 5 hours runtime. This indicates compared to the data gathered in the dataset the NPK values should still rise with increased runtime hours.

c. Genetic Algorithm Fitness Analysis

All the genetic algorithms result in a rapid convergence in the fitness scores after a certain generation. A range of factors are to be considered due to this. Firstly, the diversity of the dataset, as there are only a limited number of samples collected for the data gathering due to the test kit only having a limited number of trials. Additionally, the temporary constraints of not being able to conduct runtime tests for data gathering reach up to a day or a week. Thus, regular composting runtimes have not been fully emulated for the data gathering. The researchers have already implemented diversity mechanisms by fine-tuning the function parameters of the genetic algorithm and used artificially generated initial solutions to achieve these results. Fitness functions have been modified as well, but results have shown similar or worse outcomes. Finally, all these genetic algorithm models use a specific random seed for fair results. Thus, the results for each material also have varying NPK and compost parameter values.

CONCLUSION AND RECOMMENDATIONS

Conclusion

In the design and optimization of a Bio-Composter System using Genetic Algorithm, the researchers have the following conclusions:

- The genetic algorithm achieves realistic results in determining the best composter operational parameters for each compost material with the given target NPK values. Rotten vegetables material has the highest fitness score, and coffee grounds has the lowest. As a model suited for optimization problems, it uses global and local search to find solutions for the best composting parameters that are not present in the given dataset.
- Composter system software provides ease of use through an interface for composter control and monitoring systems. Remote capabilities also allow for convenient handling and visual representation of data. Also, users can control the system from anywhere virtually using the remote capabilities of the system.
- The motor automation of the composter system ensures consistent rotation and variable preset rotation speed.

Recommendations

1. **Enhance Data Collection and Automation**
   - Integrate advanced automation techniques, including automated extraction and cleaning, to improve system efficiency, accuracy, and sanitation while minimizing manual intervention.

2. **Improve Hardware Performance**
   - Extend the runtime durations of the Bio-Composter System to support continuous operation.
   - Upgrade motor power and adjust gear ratios to handle varying loads effectively, ensuring optimal torque and speed for enhanced composting performance.

3. **Improve Genetic Algorithm Exploration**
   - Implement and refine genetic algorithms for real-time monitoring and adjustment of composting parameters.
   - Add more controllable parameters to improve the model results, leading to more reliable and robust composting processes.

4. **Compost Material and Process Innovation**

   Investigate other compost types and production processes, including liquid compost and preprocessing techniques.

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