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วัตถุประสงค์

1. เพื่อรวบรวมและเผยแพร่ผลงานวิจัยของนักวิชาการชาวไทยและต่างชาติ โดยเฉพาะผลงานวิจัยของบุคลากรและนักศึกษาภายในคณะและมหาวิทยาลัยให้เป็นที่รู้จักในระดับชาติหรือนานาชาติ
2. เพื่อสร้างเครือข่ายนักวิชาการทั้งชาวไทยและชาวต่างชาติ
3. เพื่อเผยแพร่ชื่อเสียงของคณะและของมหาวิทยาลัย
4. เพื่อสนับสนุนการนำผลงานวิชาการและวิจัยไปใช้ประโยชน์

หน่วยงาน คณะเทคโนโลยีอุตสาหกรรม มหาวิทยาลัยนครพนม
214 หมู่ 12 ตำบลหนองญาติ อำเภอเมืองนครพนม จังหวัดนครพนม 48000
โทร. 0 4250 3777

บทบรรณาธิการ

Journal Engineering Technology Access (JETA) วารสารวิชาการ คณะเทคโนโลยีอุตสาหกรรม มหาวิทยาลัยนครพนม ฉบับนี้เป็นปีที่ 5 ฉบับที่ 1 : มกราคม – มิถุนายน 2568 มีวัตถุประสงค์เพื่อรวบรวมเผยแพร่ผลงานวิจัยของบุคลากร นักศึกษาทั้งภายในคณะ บุคคลภายนอกมหาวิทยาลัยให้เป็นที่รู้จักในระดับชาติหรือนานาชาติ และเป็นสื่อกลางในการแลกเปลี่ยนความรู้ ข้อคิดเห็นทางวิชาการและวิจัยแก่นักวิชาการ อาจารย์ นักศึกษา ตลอดจนบุคคลทั่วไปที่มีความสนใจ ด้านวิทยาศาสตร์ เทคโนโลยี วิศวกรรมศาสตร์ ครุศาสตรอุตสาหกรรม และนวัตกรรม เพื่อสร้างเครือข่ายนักวิชาการและเสริมสร้างประสิทธิภาพด้านการพัฒนางานวิจัย วารสารฉบับนี้ประกอบด้วยบทความวิจัยจำนวน 2 บทความ ซึ่งบทความทั้งหมดเป็นบทความที่น่าสนใจ และสามารถนำไป ประยุกต์ใช้กับศาสตร์ที่เกี่ยวข้องได้ ทั้งนี้ผู้ที่สนใจสามารถติดตามอ่านบทความวารสารฉบับออนไลน์ได้

วารสารฉบับนี้สำเร็จลุล่วงได้ด้วยความอนุเคราะห์จากหลายฝ่าย ประกอบด้วย บรรณาธิการบริหาร กองบรรณาธิการ ผู้ทรงคุณวุฒิภายในและภายนอก ที่กรุณาพิจารณาแก้ไขปรับปรุงบทความให้มีความสมบูรณ์และมีคุณภาพ อีกทั้งขอขอบพระคุณเจ้าของบทความทุกท่านที่ให้ความสนใจ และส่งบทความเพื่อตีพิมพ์ในวารสารฯ กองบรรณาธิการขอเชิญผู้สนใจทุกท่านร่วมส่ง บทความวิจัย และบทความวิชาการที่เกี่ยวข้องกับด้านวิทยาศาสตร์ เทคโนโลยี วิศวกรรมศาสตร์ ครุศาสตรอุตสาหกรรม และนวัตกรรม เพื่อตีพิมพ์เผยแพร่โดยไม่มีค่าใช้จ่าย และหากท่านมีข้อเสนอแนะหรือต้องการทราบข้อมูลเพิ่มเติมเกี่ยวกับวารสารฯ สามารถติดต่อได้ที่ jeta@npu.ac.th กองบรรณาธิการยินดีรับฟังข้อเสนอแนะ เพื่อเป็นประโยชน์ต่อการปรับปรุงวารสารฯ ให้มีคุณภาพดียิ่งขึ้นไป

รองศาสตราจารย์ ดร.สมชาติ โสนะแสง
บรรณาธิการ

สารบัญ

หน้า

(Research article)
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Determination of Clay Content by Applying Machine Learning with Hydrometer Testing and Specific Gravity Analyses

C. Sukkanon[1], J. Supakosol[1] and P. Chaipanna[1*]

[1]*Faculty of Industry and Technology, Rajamangala University of Technology Isan, Sakon Nakhon Campus*

pattanasak.ca@rmuti.ac.th

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Abstract

This study aims to analyze and compare hydrometer test results with fundamental soil properties while applying Machine Learning (ML), a branch of Artificial Intelligence (AI), to enhance the speed and accuracy of clay content prediction. The study utilized soil samples from Nakhon Phanom and Sakon Nakhon provinces, Thailand. The experimental process included specific gravity and hydrometer analysis. For ML model development, linear regression (LR) and random forest regressor (RFR) were compared to analyzing factors influencing clay content. The data evaluation was based on feature importance analysis and statistical correlation (Correlation Matrix). The application of 10-fold cross-validation ensured that the models did not suffer from overfitting and confirmed the stability of predictions when using hydrometer data from longer test durations. The results indicate that hydrometer readings at longer durations exhibit a strong correlation with clay content and significantly improve the prediction accuracy of LR and RFR. The highest R^2 values obtained were 0.93 for LR and 0.87 for RFR, demonstrating that longer hydrometer test durations lead to more accurate clay content predictions. ML method combined with the hydrometer readings at 180 minutes, the R^2 exceeds 0.75. Specifically, LR outperformed RFR at minute 240, suggesting that the linear model better explains data variance at this duration. This research concludes that incorporating ML with hydrometer test data significantly improves the accuracy of clay content predictions. The findings highlight the potential of ML applications in soil property analysis and geotechnical engineering design, leading to more efficient and reliable engineering solutions.

Keywords: Clay content; Hydrometer; Basic properties; Artificial Intelligence; Machine Learning

1. INTRODUCTION

The presence of high clay content in soils significantly affects the stability and integrity of engineering structures. Due to its high-water absorption and expansion properties, clayey soils undergo volumetric changes upon moisture variation, which can cause subsidence or swelling, leading to structural failures (Ural, 2018). Such soil behavior increases maintenance costs and necessitates corrective measures for infrastructure projects (Terzaghi et al., 1996).

Various methods exist for determining clay content, each with its own advantages and limitations. Sieve analysis is widely used for coarse-grained soils like sand and gravel, where particle size is determined using a series of sieves with different mesh sizes. However, sieve analysis is ineffective for particles smaller than 0.063 mm (Gee & Or, 2002), making it unsuitable for clay and silt.

Laser Diffraction Analysis is another advanced technique that measures particle size using light scattering principles. It provides rapid results with high accuracy and can analyze a broad range

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of particle sizes, from microns to millimeters (Eshel et al., 2004). However, this method requires specialized equipment and may not be cost-effective for routine laboratory testing.

The hydrometer method, established in 1927, is a sedimentation-based technique widely used to determine the particle size distribution of fine-grained soils, particularly silts and clays. This method operates on the principle of sedimentation, where soil particles suspended in a liquid settle at velocities proportional to their size, density, and the fluid's viscosity, as described by Stokes' Law (Das & Sobhan, 2018). The hydrometer measures the relative density of the suspension over time, allowing for the calculation of particle size distribution. The hydrometer method is particularly effective for analyzing fine-grained soils where traditional sieve analysis is impractical. It provides a continuous particle size distribution curve, offering detailed insights into soil composition. Additionally, it is cost-effective and standardized, making it accessible for routine soil analysis. Despite its widespread use, the hydrometer method has inherent limitations. It assumes that soil particles are spherical and of uniform density, which is often not the case in natural soils. Clay particles, for instance, are typically plate-shaped, leading to deviations from theoretical settling velocities predicted by Stokes' Law. Moreover, the method requires precise temperature control, as fluid viscosity changes can significantly affect the settling rates. The presence of dispersing agents, such as sodium hexamethaphosphate, is necessary to prevent flocculation, however, achieving complete dispersion can be challenging.

Despite advancements in soil analysis techniques, the hydrometer method remains widely used in geotechnical engineering due to its low cost, simplicity, and standardized procedures. The integration of hydrometer method and ML enhances data analysis efficiency, providing accurate predictions while reducing testing time (Vargas-Zapata et al., 2025; Zhu et al., 2018).

This research explores ML applications in soil analysis to predict clay content by investigating its relationship with specific gravity and hydrometer readings, developing and comparing Linear Regression and Random Forest Regressor models, and evaluating their performance with R2 to enhance accuracy and efficiency over traditional methods.

2. OBJECTIVES

1. To investigate the relationship between clay content and specific gravity combined with hydrometer readings at various time intervals.
2. To develop and compare ML models for clay content prediction using Linear Regression and Random Forest Regressor, evaluating their performance using the R^2 coefficient.

3. RESEARCH METHODOLOGY

3.1 Basic Soil Property Testing

The hydrometer analysis method, based on Stokes' Law, determines particle size distribution by measuring sedimentation rates in a fluid medium (ASTM D7928-17, 2017*)*. This test involves dispersing soil particles in a liquid and measuring fluid density at different depths over time using a hydrometer. Larger particles settle faster than smaller ones, allowing for particle size determination based on sedimentation rates. Stokes' Law (Das & Sobhan, 2018) defines the velocity of particle settling as:

$$d = \sqrt{\frac{18\mu Hy}{\left(G_s - G_w\right)gt}} \tag{1}$$

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where d is particle diameter (mm), μ is viscosity of water (Pa·s), Hy is the effective depth (m) of hydrometer , G_s is specific gravity of soil particles, G_w is specific gravity of water, g is gravitational acceleration and t is the time elapsed (minute)

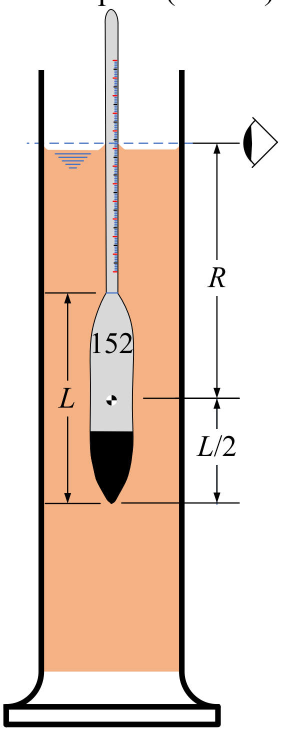

Figure 1 Hydrometer Reading

Soil samples (31 in total) were collected from Nakhon Phanom and Sakon Nakhon provinces, Thailand. Samples were sieved using a No. 40 sieve for specific gravity testing and a No. 200 sieve for hydrometer analysis, consist of both silt and clay. The hydrometer used, type 152, weighs 78 grams. Hydrometer readings (R) were recorded from 15 seconds (*Hy15s*) to 1440 minutes (*Hy1440m*) as shown in Figure 1. The effective depth (Hy) can be calculated as follows:

$$Hy = R + C_m \pm C_t - C_d \tag{2}$$

where R is the hydrometer reading, C_m is meniscus correction, C_t is temperature correction, C_d is dispersing agent correction.

3.2 Machine Learning (ML)

ML techniques were used to optimize soil property analysis. The study compared: Linear Regression (LR)**:** A simple predictive model assuming linear relationships. Random Forest Regressor (RFR)**:** An ensemble learning model that enhances prediction accuracy by averaging multiple decision trees.

3.3 Model Training and Validation

The dataset was divided using 10-Fold Cross-Validation (Scikit-learn, 2025) to ensure stability and prevent overfitting. The data distribution for Cross-Validation is shown in Figure 2.

3.4 Data Analysis and Interpretation

Table 1 summarizes the statistical properties of the clay content, specific gravity, and hydrometer readings at different time intervals, providing an overview of the variation in the soil samples used for analysis.

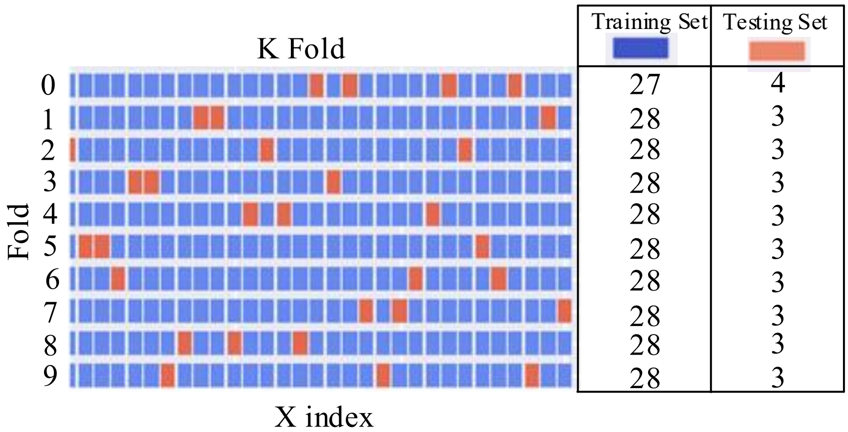

Figure 2 Cross-Validation

The mean clay content is 23.55% with a standard deviation of 14.04, indicating a moderately high variation in soil properties across samples. The minimum (9.09%) and maximum (61.95%) values suggest a significant disparity in clay content among samples, which could be attributed to variations in sampling locations. The high standard deviation implies that the dataset includes a mixture of different soil classifications, ranging from sandy silt to highly clayey soils.

The specific gravity values show a narrow range (Min = 2.55, Max = 2.75) with a low standard deviation (0.06). These values are within the expected range for typical clay and silt soils (2.6 - 2.8) (Holtz et al., 2011), confirming the dataset's reliability. Since G_s remains relatively stable, it may not be a dominant predictor variable in *ML* models but serves as a secondary feature to improve predictions.

As expected, the hydrometer readings decrease over time, demonstrating sedimentation of fine particles. Initial readings (*Hy15s* = 52.05% mean) are the highest due to suspended fine particles, whereas *Hy1440m* = 10.67% mean indicates the final settling phase. High standard deviations at earlier times (e.g., *Hy5m* = 6.20, *Hy10m* = 6.97) suggest substantial variation in soil suspension behavior among samples. At *Hy420m* and *Hy180m*, variability decreases, indicating that these time points may be more stable for modeling clay content.

Table 1 Statistical data for data analysis

Variables	Count	Mean	Std	Min	25%	50%	75%	Max
Clay	31	23.55	14.04	9.09	12.96	18.75	28.25	61.95
G_s	31	2.65	0.06	2.55	2.60	2.65	2.69	2.75
Hy15s	31	52.05	1.88	47.81	51.13	51.88	52.81	57.81
Hy30s	31	49.12	1.94	44.44	48.00	48.81	50.03	53.19
Hy1m	31	46.25	2.82	38.44	44.16	46.81	48.00	51.19
Hy2m	31	41.31	5.33	21.44	39.00	41.88	45.19	48.19
Hy5m	31	35.54	6.20	18.44	32.00	35.81	39.34	46.19
Hy10m	31	29.92	6.97	15.44	23.97	30.19	34.81	44.19
Hy20m	31	24.86	8.41	10.19	17.47	25.88	31.81	41.19
Hy40m	31	20.41	8.62	6.81	12.62	21.88	25.81	40.19

Variables	Count	Mean	Std	Min	25%	50%	75%	Max
Hy80m	31	17.40	8.58	6.81	10.50	15.81	21.84	39.19
Hy180m	31	15.28	8.36	5.81	7.88	12.81	20.31	35.57
Hy240m	31	14.62	7.94	5.81	7.53	12.13	19.81	33.57
Hy420m	31	13.10	7.15	4.81	7.38	11.19	15.88	33.57
Hy1440m	31	10.67	6.00	4.50	7.03	8.81	12.65	32.57

3.5 Performance Measurement

In evaluating the predictive accuracy of *ML* models, particularly in regression problems, a key performance measures metric is commonly used. R-Squared (R^2) (Gao, 2024) metric quantifies the proportion of variance in the dependent variable (e.g. clay) that is explained by the independent variable (e.g. hydrometer readings as different times). It is defined as:

$$R^2 = 1 - \frac{\sum\left(y_i - y_i\right)^2}{\sum\left(y_i - \bar{y}_i\right)^2} \tag{3}$$

where y_i is actual observed values, y_i is predicted values from the model, $\bar{y}_i$ is mean of actual observed values

Interpretation of R^2 values:

$R^2 = 1$ Perfect prediction (model explains 100% of the variance)
$R^2 = 0$ Model does not explain any variance beyond the mean prediction
$R^2 < 0$ The model performs worse than a simple mean predictor.

4. RESEARCH RESULTS

4.1 Importance and Correlation of Feature

In Figure 3, the RFR model was utilized to evaluate the importance of various features in predicting clay content. The analysis showed that the most influential variables for predicting clay content were hydrometer readings taken at longer durations, specifically at *Hy420m*, *Hy1440m*, *Hy240m*, and *Hy180m*. These durations exhibited higher feature importance than the physical property of specific gravity (G_s), which was found to have a moderate effect. In contrast, the shorter hydrometer durations such as *Hy15s*, *Hy30s*, and *Hy1m* demonstrated low importance, indicating that they had a minimal contribution to accurate predictions of clay content.

The correlation matrix further supported these findings. It revealed a strong relationship between clay content and hydrometer readings at longer durations, especially at *Hy180m* with an R^2 value close to 0.9, as shown in Figure 4. This suggests that longer hydrometer test durations provide more reliable predictions for clay content. On the other hand, shorter durations like *Hy15s*, *Hy30s*, and *Hy1m* showed significantly weaker correlations, reinforcing the idea that selecting longer durations such as *Hy180m*, *Hy80m*, and *Hy240m* for feature inclusion can improve the model's predictive performance.

4.2 Accuracy of the Analysis

As shown in Figure 5, the evaluation of the ML models for predicting clay content was conducted through R^2, using 10-Fold Cross-Validation to reduce overfitting. The experimental results indicate that the selection of hydrometer test durations directly affects the performance of the models. The comparison of two datasets is as follows:

- **Dataset 1**: Uses values from *Hy15s* to *Hy420m*
- **Dataset 2**: Uses values from *Hy10m* to *Hy420m*

It was found that the highest R^2 value occurred at *Hy180m*, where the RFR gave an R^2 value of 0.92 and LR gave an R^2 value of 0.85. This means that RFR explains the data variance best at *Hy180m*, whereas shorter durations, such as *Hy10m*, gave lower R^2 values, with some even being

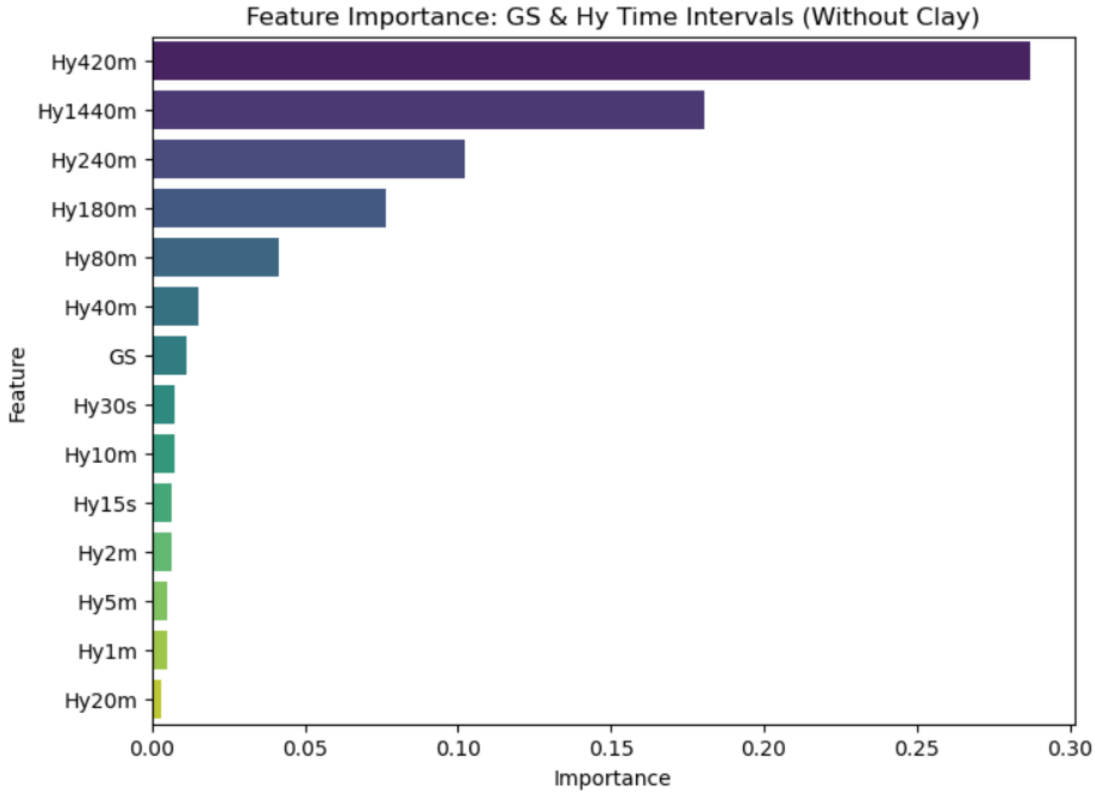

Figure 3 Feature Importance

negative, indicating poor prediction accuracy. Longer durations, such as Hy180m, allow for complete sedimentation of fine particles, leading to a more measurement of clay content. This is supported by stdud

Using data starting from *Hy10m* onwards gave higher prediction accuracy compared to datasets with shorter durations like *Hy15s* or *Hy30s*, which showed lower and unstable R^2 values. The selection of *Hy180m* as the most appropriate duration was based on a combination of three key factors:

1. Feature Importance (Figure 3)
   - Although *Hy420m* and *Hy1440m* had the highest feature importance, *Hy180m* also had a high importance value.
   - Selecting *Hy180m* reduced the testing time without sacrificing model accuracy.
2. Correlation Matrix (Figure 4)
   - *Hy180m* had a high correlation with clay content (0.83), demonstrating that this time still accurately reflects the soil properties without needing a longer duration.
3. R^2 Comparison Graph (Figure 5)
   - *Hy180m* showed the highest R^2 within the appropriate duration (0.92 for RFR and 0.85 for LR). R^2 values greater than 0.7 are acceptable in research (Musafar et al., 2023).

- It reduced testing time from *Hy420m* while maintaining high accuracy.
- At 240 minutes, the data followed a more linear trend, which made LR better suited to explain the variance in clay content, RFR, while poerful for non-linear data did not perform as well at this duration due to linear nature of the data.

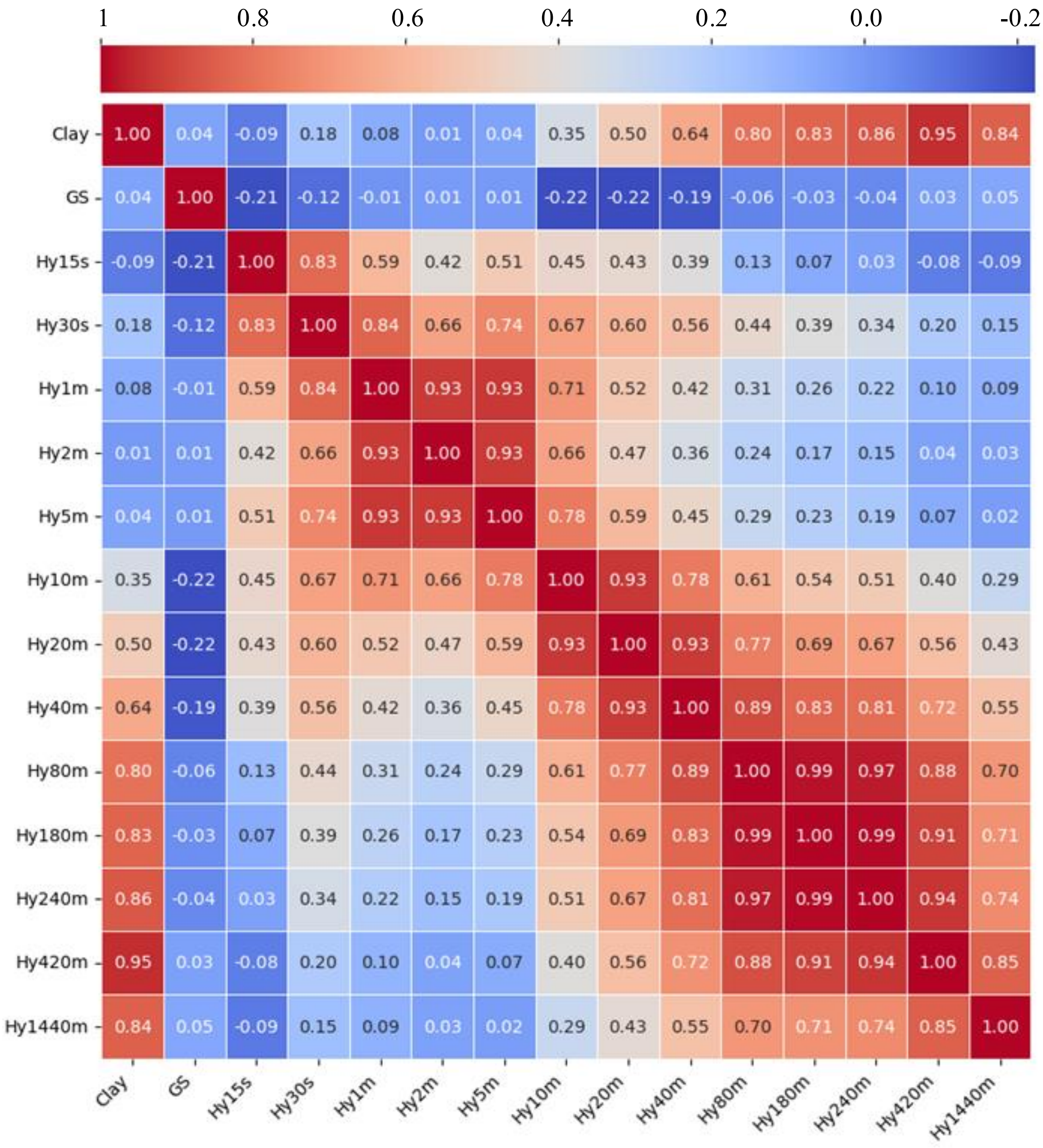

Figure 4 Correlation Matrix

Model Tuning and Reducing Testing Duration The results showed that using *Hy180m* reduced the testing duration compared to *Hy420m* while maintaining the highest accuracy. Choosing the period from *Hy10m* to *Hy180m* as input variables (Feature Selection) helped reduce model complexity and increased testing speed without compromising prediction accuracy. Additionally, using 10-Fold Cross-Validation ensured that the models were not overfitting and could predict new data accurately.

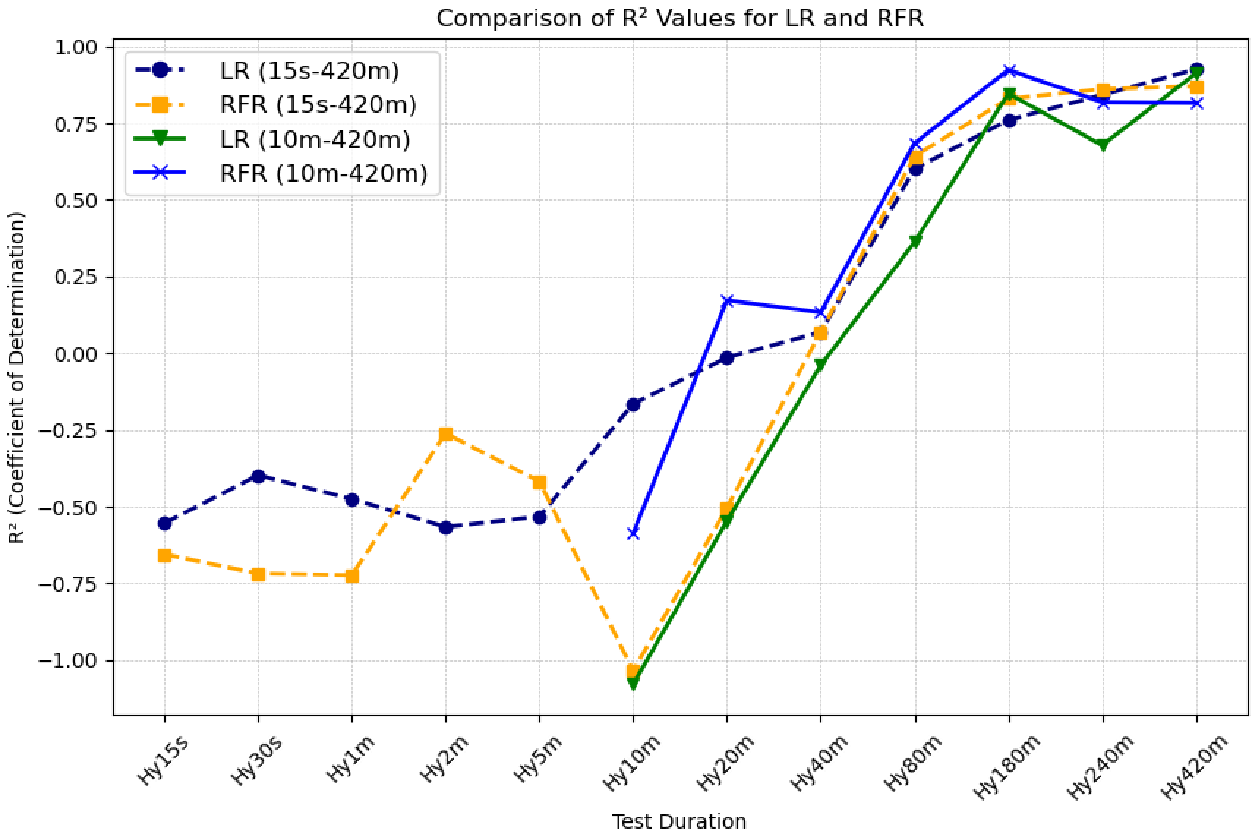

Figure 5 Performance comparison of LR and RFR models

5. CONCLUSIONS

This study investigates the integration of ML techniques with hydrometer testing to enhance the prediction of clay content in soils. The research compares two ML models LR and RFR to determine their effectiveness in predicting clay content using specific gravity (Gs) and hydrometer readings at various time intervals. Key Findings:

- Hydrometer Readings Influence Prediction Accuracy: Longer hydrometer test durations (e.g., *Hy180m*, *Hy240m*, *Hy420m*) showed a stronger correlation with clay content. The highest R^2 values were 0.87 for LR and 0.93 for RFR, demonstrating the importance of selecting the optimal test duration. The ML method combined with Hy180m readings resulted in R^2 exceeding 0.75, making it an effective balance between test duration and prediction accuracy.
- Model Performance Comparison: RFR outperformed LR in handling complex data and reducing prediction errors. LR performed best at *Hy240m*, suggesting it is better suited for cases where a linear relationship is dominant. Shorter hydrometer durations (e.g., *Hy15s*, *Hy30s*) showed low feature importance and weak correlation with clay content.
- Feature Selection and Model Optimization: Removing low-correlation variables improved model efficiency while reducing overfitting risks. 10-Fold Cross-Validation ensured stable predictions.

The study confirms that integrating ML with hydrometer analysis significantly improves clay content prediction accuracy, reducing testing time while maintaining reliability. The findings support ML applications in geotechnical engineering for more efficient and precise soil property analysis.

6. FUTURE RESEARCH DIRECTIONS

- Expanding ML models to include Deep Learning (e.g., ANN, CNN, RNN) for more complex soil behavior prediction.
- Develop a software tool or web application that integrates ML models for real-time predictions of clay content in the field.
- Integration of additional soil properties such as Atterberg limits, compaction characteristics, and mineral composition to improve predictive models.
- Developing explainable AI techniques to enhance model interpretability for engineering applications.

7. ACKNOWLEDGEMENTS

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IoT-Based Intelligent Environmental Control for Minimizing Spring Onion Bulb Weight Loss: A Grey-Taguchi Optimization

A. Kaewchaloon[1], K. Komanee[1], S. Charonerat[1]

P. Thosa[1] , S. Prasomthong[1]*

[1,2,3,4,5]*Faculty of Industrial Technology, Nakhon Phanom University*

Nakhon Phanom, Thailand, 48000.

E-mail: Suriya.p@npu.ac.th

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ABSTRACT

Post-harvest deterioration of spring onion bulbs presents a significant challenge for smallholder farmers in regions like Nakhon Phanom, Thailand, where high ambient temperatures and fluctuating humidity accelerate crop quality loss. These environmental instabilities contribute to substantial economic losses due to reduced shelf life and market value. This study proposes an integrated solution by developing an Internet of Things (IoT) based intelligent environmental control system, optimized using the Grey-Taguchi L9 method, to minimize weight loss during storage. The experimental setup evaluated nine distinct environmental conditions comprising different combinations of temperature, relative humidity, and light intensity over a three-month storage period. The IoT system enabled real-time monitoring and automated adjustments of key environmental parameters through embedded sensors and actuators. Statistical analysis, including signal-to-noise (S/N) ratio calculations and Grey Relational Analysis (GRA), was employed to determine optimal storage conditions. The results demonstrated that temperature and relative humidity were the most influential factors affecting weight loss, with optimal settings identified as 20°C and 65% RH, respectively. Under these conditions, average weight loss was minimized to 5.2 grams, and the model achieved a high R-squared value of 99.74%. In contrast, light intensity was found to have a negligible effect. This research offers a practical and scalable post-harvest solution for resource-constrained agricultural communities. By combining low-cost IoT technology with multi-response optimization, the proposed system contributes to sustainable agriculture and enhances food security by reducing storage-related losses in perishable crops.

Keyword: IoT, Grey-Taguchi Optimization, Minimizing Spring Onion Bulb

1. INTRODUCTION

Spring onions are an important agricultural product in Nakhon Phanom, However, post-harvest losses can exceed 30 - 40% under uncontrolled storage conditions, leading to reduced income for farmers and increased volatility in supply chains. These losses directly impact household level economic stability and pose broader challenges to food security in developing agricultural regions. where the local economy benefits significantly from their cultivation and trade. However, a critical challenge faced by farmers in this region is the preservation of harvested spring onion bulbs, particularly under fluctuating environmental conditions that can reduce product quality, shelf life, and market value. Traditional storage methods often lack the necessary environmental controls to maintain optimal conditions for long-term preservation, leading to post-harvest losses.

The integration of modern technologies, such as the Internet of Things (IoT), into agricultural practices provides a promising solution to this issue. IoT technology enables real-time monitoring and adjustment of critical environmental parameters, such as temperature, humidity, and light intensity, which are known to affect the longevity and quality of stored crops. In this study, an IoT-based intelligent monitoring and control system was developed, consisting of sensors for environmental data acquisition, a microcontroller for processing, and actuators such as fans, humidifiers, and LED lighting to adjust the storage environment automatically. The system also includes a user interface connected via mobile application or web dashboard, allowing remote monitoring and alert notifications. An overview of this system is illustrated in Figure 1.

Despite this potential, limited research has been conducted on the application of IoT technology specifically for optimizing the storage of spring onion bulbs in rural farming communities like those in Nakhon Phanom, where infrastructure and resources may be limited.

Several studies have explored the role of IoT technologies in post-harvest management. For instance, Zhang et al. [1] implemented an Industrial IoT-based system to regulate temperature and gas composition in crop storage in southern China, achieving reduced spoilage rates. However, such systems often rely on expensive infrastructure or industrial-scale implementation, which limits their feasibility in rural or smallholder farming contexts. Moreover, few studies have integrated IoT with robust multi-response optimization approaches to address complex storage environments. While existing studies have explored IoT applications in agriculture, most focus on crop growth monitoring and irrigation systems, with fewer studies addressing the post-harvest storage phase. Previous research has identified the significance of environmental factors, particularly temperature and humidity, in post-harvest storage, but the application of IoT-based systems for controlling these variables remains underexplored in the context of spring onion bulb storage. Additionally, studies using optimization methods like the Taguchi approach have been widely applied in engineering fields to enhance process efficiency [2], yet their use in agricultural storage systems, particularly in combination with IoT technologies, is scarce.

This research addresses this gap by employing a Grey-Taguchi L9 [3-6] optimization method to control key environmental factors in an IoT-monitored storage system, thereby contributing to both the agricultural and engineering fields. This research is among the first to integrate an IoT-based environmental control system with Grey-Taguchi L9 optimization for post-harvest spring onion storage, particularly targeting low-resource agricultural settings its application of the Grey-Taguchi L9 method for optimizing storage conditions of spring onion bulbs, which has not been previously addressed in the literature. By focusing on the variables of temperature, relative humidity, and light intensity, this study establishes optimal environmental settings for preserving onion bulbs using an IoT-based intelligent monitoring system.

The proposed approach not only advances the understanding of post-harvest storage solutions but also provides a practical, scalable solution for small-scale farmers in Nakhon Phanom. The combination of IoT technology with a structured optimization method offers a significant contribution to both the agricultural technology and environmental control fields, with implications for improving post-harvest practices in similar agricultural regions.

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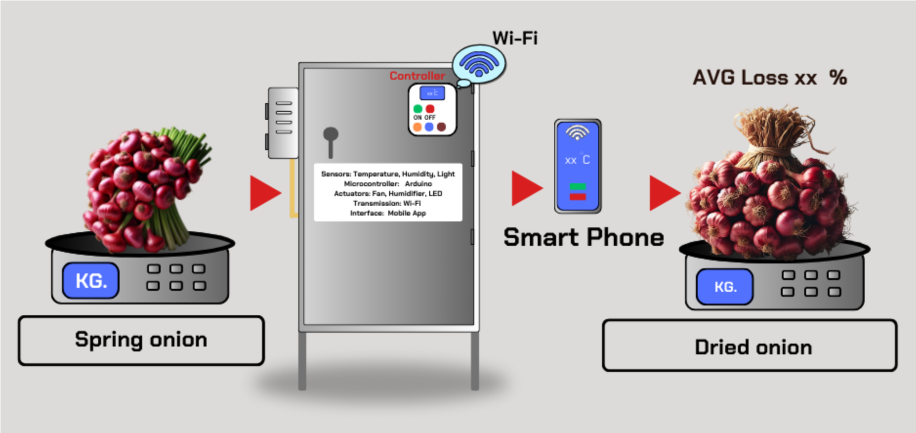

Fig. 1 Schematic of the IoT-Based Monitoring and Control System for Spring Onion Storage

2. LITERATURE REVIEW

2.1 IoT Applications in Agricultural Storage Systems

The integration of Internet of Things (IoT) technologies into agricultural storage systems has emerged as a transformative approach to enhance the efficiency of post-harvest processes and improve the overall storage environment. Recent studies have focused on how IoT can be utilized to monitor and manage critical factors that influence crop preservation, providing real-time data that aids in decision-making and management. These IoT systems offer the potential to address some of the most pressing challenges in agricultural storage, such as spoilage and inefficient management, by creating smarter and more responsive storage environments.

A recent study by Zhang, Lin, and Jiao [1] explored the design of an intelligent storage management system tailored for the specific needs of crop storage in southern Xinjiang, China. The system employed Industrial Internet of Things (IIoT) technologies to gather real-time environmental data, including temperature, humidity, and gas levels, within storage facilities. The gathered data was then transmitted to a centralized platform, where it could be remotely monitored and managed through a mobile application. This approach allowed for real-time adjustments in storage conditions and enabled predictive analytics to preemptively address issues before they negatively impacted stored crops. The ability to remotely manage storage conditions significantly improved operational efficiency, reducing the likelihood of crop spoilage due to environmental factors. This research underscores the critical role that IoT plays in improving agricultural storage systems, especially in regions where environmental conditions pose significant challenges to maintaining crop quality during storage.

The growing implementation of IoT in agriculture storage systems provides innovative solutions for maintaining the quality of stored agricultural products. By continuously monitoring environmental conditions, these systems enable precise control over factors that could otherwise lead to spoilage or degradation of crops. Consequently, IoT-driven storage management systems are proving to be a valuable tool in securing sustainable and efficient agricultural practices in various regions.

2.2 Post-Harvest Management and Storage of Spring Onions

Post-harvest management and storage of onions, including spring onions, are critical aspects that directly influence the longevity, quality, and marketability of the produce. Proper storage conditions can significantly reduce post-harvest losses, which in some cases exceed 40%, by ensuring optimal temperature, humidity, and ventilation. These factors help prevent physiological deterioration and weight loss, which are major contributors to onion spoilage. Technological advancements in onion storage have shown promising results in extending the shelf life of onions, thus supporting agricultural sustainability, and enhancing economic benefits by improving the consistency of supply and reducing market fluctuations [8]. A study by Abate [2] focused on the effect of storage temperature on the physicochemical quality attributes of Bombay Red onion bulbs. The research concluded that storing onions at a lower temperature, specifically 5°C, helped maintain their quality over six months, while higher temperatures (25°C) led to more rapid quality deterioration. This finding underscores the importance of maintaining cool, controlled storage conditions to reduce post-harvest losses. Additionally, studies have shown that onion maturity and the method of harvest also play significant roles in post-harvest quality. For instance, harvesting without irrigation and allowing onions to cure in the field for a few days significantly improved their weight retention and minimized weight loss during storage. This approach is particularly effective for maintaining onion quality over extended storage periods [9].

Moreover, research conducted by Davletbaeva et al. [7] emphasized the need for maintaining low-temperature regimes around 12°C and relative humidity between 75-80% to preserve onion quality. The physiological maturity of the bulbs, indicated by fully dried outer scales and high sucrose content, was also found to be crucial for extending their storage life. These insights suggest that understanding the specific requirements for post-harvest storage, including maturity and environmental control, is essential for minimizing losses and maintaining onion quality during prolonged storage periods. In conclusion, post-harvest management of onions requires a comprehensive approach that considers storage conditions, maturity at harvest, and appropriate curing methods. Technological improvements in storage systems, combined with optimized harvesting practices, offer significant potential to reduce post-harvest losses and ensure better-quality onions throughout the supply chain.

2.2 Optimization Techniques for Environmental Control in Agricultural Systems

Optimization techniques for environmental control in agricultural systems have become increasingly important as the sector seeks to address challenges such as resource efficiency, sustainability, and climate variability. A range of advanced methods, including neural networks, fuzzy logic, and multi-stage optimization, are being employed to optimize the use of water, energy, and other critical resources, while maintaining optimal conditions for crop growth. One approach focuses on improving soil moisture management using neural networks. By integrating automated control systems that adapt to weather variability, this method ensures efficient water and energy use, ultimately enhancing crop yields while conserving resources [12]. Such techniques are crucial for ensuring that agricultural operations are both sustainable and economically viable. In another application, an intelligent irrigation system is used to measure the precise water demand of crops, thus minimizing waste, and addressing water scarcity. The system, implemented in a smart greenhouse environment, uses sensors and actuators to maintain optimal temperature and humidity levels, further optimizing crop conditions [11].

Additionally, a multi-stage farm management optimization model has been proposed to incorporate both crop rotation and environmental constraints. By using mixed-integer linear programming, this model seeks to maximize farm profitability while adhering to environmental standards, such as reducing greenhouse gas emissions [10]. This demonstrates how optimization techniques can address both economic and environmental goals in agriculture. The application of intelligent automation technologies, such as GPS-enabled tractors and drone farming, also plays a critical role in advancing agricultural sustainability. These technologies, combined with computational intelligence methods like artificial neural networks, improve the effectiveness of mechatronic systems for environmental control, such as water management [14]. Finally, fuzzy control methods, when applied to hydroponic systems, have shown to improve the quality of crops such as strawberries. By regulating key environmental factors, this method ensures more efficient use of resources and enhances plant growth, yielding greater foliage and larger fruits compared to traditional cultivation methods [13]. These examples illustrate the growing role of advanced optimization techniques in enhancing the sustainability and efficiency of agricultural systems, with positive impacts on both food production and environmental conservation.

3. EXPERIMENTAL METHOD

3.1 Data collection methods

The data collection for this experiment began with the preparation of spring onion bulbs of consistent size and weight. Each experimental run in the L9 orthogonal array was conducted in triplicate (n = 3) to account for experimental variability and to ensure statistical reliability. The results from the three replicates were averaged, and the standard deviation was calculated to assess data consistency. The bulbs used in the experiment had an initial constant weight of 1 kilogram, and the data collection period was set to 3 months. The spring onion bulbs were divided into 9 groups according to the experimental design outlined in the L9 orthogonal array. Initial weight measurements were taken for each group before placing them into the storage facility, and the recorded initial weights were noted. Subsequently, an automated system in the storage facility was set up according to the factors specified for each trial in the L9 array, allowing the spring onion bulbs to be stored for the specified duration in each experimental set. At the end of the storage period, the weight of each group of spring onion bulbs was measured again, and the post-experiment weights were recorded. All experimental runs were monitored using an IoT-based system that integrated multiple environmental sensors and actuators. The primary sensors included a DHT22 digital sensor for temperature and humidity measurement (±0.5°C, ±2% RH accuracy) and a BH1750 sensor for light intensity (lux level). These sensors were calibrated according to the manufacturer's protocols prior to the experiment. Data were collected at 5-minute intervals using an ESP32 microcontroller platform, which enabled wireless transmission of data to a cloud server via Wi-Fi. The data logging and dashboard interface were managed using the Blynk platform, allowing remote monitoring and notification alerts for out-of-range parameters. Weight loss for each group was calculated using a predefined formula by subtracting the post-experiment weight from the initial weight. After obtaining the weight loss data, the results from all 9 experimental sets were analyzed to determine which factors had the most significant impact on weight loss, using statistical analysis based on the Taguchi method.

3.2 Experimental design

This operation commenced with a review of relevant literature concerning the design of an intelligent environmental control system, which includes regulating temperature, humidity, and light that impact the storage of shallot bulbs. The focus was on designing a suitable storage facility specifically for shallot bulbs. Following the literature review, fieldwork was conducted to investigate the issues faced by shallot farmers. This included collecting data through interviews, observations, and focus group discussions on factors affecting the quality of shallot bulb storage, such as temperature, relative humidity, and light intensity. These findings were then applied to develop and design a storage facility utilizing an intelligent environmental control system. Upon completing the design phase, sensors and control units were installed to regulate temperature, humidity, and light within the facility. This system is capable of real-time monitoring, and if environmental conditions become unsuitable, the system automatically adjusts to maintain optimal

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conditions. Furthermore, an alert system was integrated to notify users of any malfunctions, ensuring timely intervention. Subsequently, experiments were conducted to examine the effects of the automated system on shallot bulb weight loss, employing the Taguchi L9 experimental design. This method tested various factors that influence weight loss, including temperature, relative humidity, and light intensity, as illustrated in **Table 1**. The storage chamber was constructed from insulated panels to minimize external heat transfer. Sensors were mounted at bulb level to closely monitor the microenvironment around the samples. Actuators included a 12V DC fan for airflow control, a PTC ceramic heater for temperature regulation, an ultrasonic humidifier for RH adjustment, and LED arrays for light intensity control. The control logic was implemented on the ESP32 using Arduino IDE, with thresholds defined by each L9 configuration. When environmental parameters deviated from set points, the controller automatically triggered the corresponding actuator to restore balance. The experimental results revealed which factors had the most significant impact on reducing weight loss in shallot bulbs, with the experimental framework shown in **Figure 1**.

3.3 Taguchi grey relational analysis

A. Taguchi Grey Relational Analysis (GRA), the procedure involves transforming experimental data into a comparable sequence (normalization), followed by Grey Relational Coefficient (GRC) calculation, and finally, Grey Relational Grade (GRG) computation to optimize multi-response problems. Below is an outline of the main equations used in this method. The experimental data must be normalized before applying the GRA method. Depending on the goal (whether smaller values are better), the following normalization equations are used 1 [6].

$$x_i(k) = \frac{\max(X_i(k)) - X_i(k)}{\max(X_i(k)) - \min(X_i(k))} \tag{1}$$

Where:

$X_i(k)$ is the original response value for the i^{th} experiment and k^{th} performance characteristic.
$x_i(k)$ is the normalized value of the i^{th} experimental result for k^{th} performance characteristic.

The Grey Relational Coefficient is calculated to express the relationship between the ideal and actual normalized experimental data. The formula is 2

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta \cdot \Delta_{\max}}{\Delta_i(k) + \zeta \cdot \Delta_{\max}} \tag{2}$$

Where: $\xi_i(k)$ is the Grey Relational Coefficient for the i^{th} experiment and k^{th} response.
$\Delta_i(k) = |x_0(k) - x_i(k)|$ is the absolute difference between the reference sequence (ideal normalized value) $x_0(k)$ and the normalized experimental value $x_i(k)$.
Δ_{min} and Δ_{max} are the minimum and maximum values of $\Delta_i(k)$, respectively.
ζ is the distinguishing coefficient, typically between 0 and 1(commonly set at 0.5).

The Grey Relational Grade is calculated as the average of the Grey Relational Coefficients for each performance characteristic. This provides a single value that represents the overall performance of each experiment in relation to the optimal result 3

$$\gamma_i = \frac{1}{m} \sum_{k=1}^{m} \xi_i(k) \tag{3}$$

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Where: γ_i is the Grey Relational Grade for the i^{th} experiment.
m is the number of performance characteristics (responses).
ξ_i(k) is the Grey Relational Coefficient for the k^{th} response.

4. EXPERIMENTAL RESULTS

4.1 Taguchi Analysis

Table 2 presents the results of an experiment designed to evaluate the effects of temperature, relative humidity, and light intensity on the weight loss of onions. The experiment consists of nine different runs, each involving a unique combination of the three variables. Temperature was tested at three levels: 20°C, 25°C, and 30°C. Similarly, relative humidity levels of 60%, 65%, and 70% were employed, while light intensity varied between 4 and 6 KJ/m². The weight loss of the onions in grams was measured for each combination of these factors, As each condition was replicated three times, the values presented in Table 2 represent mean values. Standard deviations were also computed to assess the variation within replicates. alongside the calculation of the Signal-to-Noise Ratio (SNR) for each run. SNR helps to optimize the experiment by indicating the robustness of the process under different conditions. In this case, more negative values of SNR suggest greater weight loss, which is an undesirable outcome for onion preservation. The data in Table 2 shows that as the temperature and humidity increase, particularly at 30°C and 70% relative humidity, the weight loss becomes more severe, with Run 9 showing the highest average of weight loss of 11.6 grams and the lowest SNR (-21.29).

Table 2. Results of the onion weight loss experiment.

Run	Temperature (C^o)	Relative humidity (%)	Light intensity (KJ/m^2)	Weight loss Mean ± SD (g)	SNRA
1	20	60	4	5.8	-15.27
2	20	65	6	5.2	-14.32
3	20	70	8	6.1	-15.71
4	25	60	6	7.4	-17.38
5	25	65	8	6.6	-16.39
6	25	70	4	8.7	-18.79
7	30	60	8	9.6	-19.65
8	30	65	4	8.7	-18.79
9	30	70	6	11.6	-21.29

Table 3 offers insight into the statistical analysis of the experiment's results by showing the estimated model coefficients for the SN ratios. These coefficients indicate the influence of each experimental factor (temperature, relative humidity, and light intensity) on the SNR, and thus on onion weight loss. The table displays both the coefficient values and their corresponding standard errors, along with t-statistics and p-values to assess the significance of each factor. A positive coefficient suggests that an increase in that factor improves the SNR, thereby reducing weight loss. The analysis reveals that temperature at 20°C and relative humidity at 65% have a significant positive effect on reducing weight loss, with their p-values (0.004 and 0.023, respectively) indicating strong statistical significance. On the other hand, factors such as light intensity and relative humidity at 60% are not statistically significant, as indicated by their higher p-values, suggesting these factors have little to no effect on the weight loss of onions.

The R-squared value of 99.48% demonstrates that the model explains nearly all of the variability in the SN ratios, which reflects a very strong fit. The adjusted R-squared value of 97.94%

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further supports the model's robustness by accounting for the number of predictors used in the analysis. Overall, the results suggest that controlling temperature and humidity can effectively reduce onion weight loss, while light intensity does not appear to have a meaningful impact under the tested conditions. This insight provides valuable information for optimizing the storage conditions of onions to minimize weight loss.

Table 3 Estimated Model Coefficients for SN ratios

Term	Coef	SE Coef	T	P
Constant	-17.5096	0.1094	-160.008	0.000
Temperature 20	2.4112	0.1548	15.580	0.004
Temperature 25	-0.0124	0.1548	-0.080	0.943
Relative 60	0.0767	0.1548	0.496	0.669
Relative 65	1.0091	0.1548	6.521	0.023
light in 4	-0.1069	0.1548	-0.691	0.561
light in 6	-0.1551	0.1548	-1.002	0.422

S = 0.3283, R-Sq = 99.48 %, R-Sq(adj) = 97.94 %

Table 4 provides an Analysis of Variance (ANOVA) for the Signal-to-Noise (SN) ratios from the onion weight loss experiment. This analysis helps to determine the significance of the effects of the three experimental factors temperature, relative humidity, and light intensity on the weight loss of onions. The table includes key statistical metrics such as the sum of squares (Seq SS), mean squares (Adj MS), F-ratios (F), p-values (P), and the percentage contribution of each factor to the total variance. The degrees of freedom (DF) column indicate the number of levels for each factor minus one. For each of the three factors temperature, relative humidity, and light intensity DF is 2 since each factor was tested at three levels. The sum of squares (Seq SS) represents the variation explained by each factor. Temperature has the highest Seq SS value of 34.7036, indicating that it explains the largest amount of variation in the SN ratios. Relative humidity follows with a Seq SS of 6.6096, while light intensity has a very small value of 0.3122, indicating it contributes minimally to the overall variation. The residual error, representing unexplained variation, is quite small with a Seq SS of 0.2155, further indicating that the experimental model accounts for most of the variation in the results.

Table 4. Analysis of Variance for SN ratios of Weight loss (g)

Source	DF	Seq SS	Adj SS	Adj MS	F	P	% Contribution
Temperature	2	34.7036	34.7036	17.3518	161.00	0.006	82.94
Relative humidity	2	6.6096	6.6096	3.3048	30.66	0.032	15.79
light intensity	2	0.3122	0.3122	0.1561	1.45	0.408	0.74
Residual Error	2	0.2155	0.2155	0.1078			0.51
Total	8	41.8410					100

The adjusted mean square (Adj MS) is the Seq SS divided by the DF, and it represents the average variation for each factor. The F-ratio (F) is the ratio of Adj MS for each factor to the Adj MS for residual error, used to determine the statistical significance of each factor's effect. A larger F value indicates a more significant effect. In this table, temperature has an F-ratio of 161.00, which is much higher than the critical value, suggesting that temperature has a highly significant impact on onion weight loss. Similarly, relative humidity has a significant F-ratio of 30.66. However, light intensity, with an F-ratio of 1.45, does not have a significant effect, as its p-value (0.408) exceeds the typical significance threshold of 0.05. The p-values confirm the statistical significance of the factors. Temperature and relative humidity have p-values of 0.006 and 0.032, respectively, both of which are below 0.05, indicating they significantly affect the SN ratios. Light intensity, with a p-value of 0.408, is not statistically significant. The percentage contribution column quantifies how much each factor contributes to the total variation in the experiment. Temperature has the highest contribution, accounting for 82.94% of the total variance, making it the most influential factor. Relative humidity contributes 15.79%, which also plays a significant role, though much less than temperature. Light intensity contributes only 0.74%, while the residual error accounts for just 0.51% of the variation, confirming that the experimental model is robust and well-suited for explaining most of the variance in weight loss. Overall, the results from the ANOVA clearly show that temperature and relative humidity are the key factors influencing onion weight loss, while light intensity has a negligible effect.

Table 5. Response Table for Signal to Noise Ratios (Smaller is better) of weight loss (g)

Level	Temperature	Relative humidity	Light intensity
1	-15.10	-17.43	-17.62
2	-17.52	-16.50	-17.66
3	-19.91	-18.60	-17.25
Delta	4.81	2.09	0.42
Rank	1	2	3

Table 5 presents the response table for the Signal-to-Noise (SN) ratios, indicating the effects of temperature, relative humidity, and light intensity on onion weight loss, where a smaller value is considered better. The table breaks down the SN ratios at three levels for each factor. For temperature, the SN ratio increases (less negative) as the temperature decreases, with the lowest SN ratio (-19.91) occurring at Level 3 (30°C) and the highest (-15.10) at Level 1 (20°C). This shows that weight loss is minimized at lower temperatures. The Delta value (the difference between the maximum and minimum SN ratios) for temperature is 4.81, making it the most influential factor with Rank 1. Relative humidity follows with a Delta of 2.09, where the highest SN ratio (-16.50) is at Level 2 (65%) and the lowest (-18.60) at Level 3 (70%). This suggests that a relative humidity of 65% minimizes weight loss. Light intensity has the smallest Delta value of 0.42, indicating it has the least impact on weight loss (Rank 3). The SN ratios for light intensity are quite similar across all levels, showing minimal variance between the different light intensities tested. In summary, temperature has the greatest effect on reducing weight loss, followed by relative humidity, while light intensity has a negligible impact.

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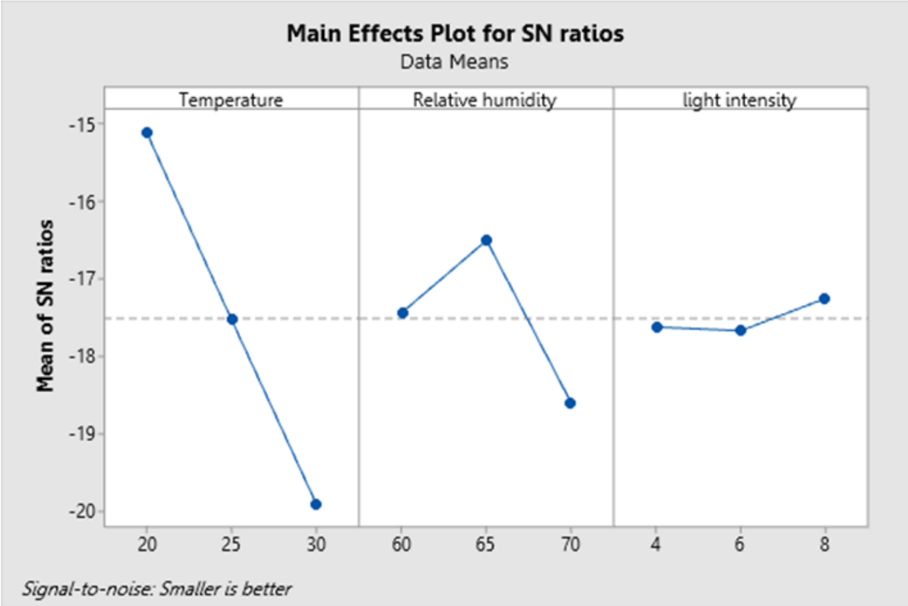

Figure 2. Main Effects Plot of SN ratios of weight loss (g)

Figure 2 shows the Main Effects Plot for SN ratios, illustrating the influence of temperature, relative humidity, and light intensity on onion weight loss. The y-axis represents the mean SN ratio, and since "smaller is better," more negative SN ratios indicate better performance in minimizing weight loss. The plot for temperature shows a clear downward trend as the temperature increases, indicating that higher temperatures lead to more weight loss. The SN ratio decreases significantly from -15.10 at 20°C to -19.91 at 30°C, making temperature the most impactful factor. For relative humidity, the plot shows a slight rise at 65%, with the mean SN ratio improving to -16.50. However, at 70%, the SN ratio drops again to -18.60, indicating that 65% relative humidity is the optimal level for minimizing weight loss. The plot for light intensity shows relatively flat results, with only minor variations between levels. The SN ratios stay around -17.5 to -17.25, confirming that light intensity has the least effect on weight loss compared to the other two factors. Overall, temperature has the most significant impact on the SN ratio, followed by relative humidity, while light intensity shows minimal effect in this experiment.

4.2 Grey Relational Analysis (GRA)

Table 6 presents the results of Grey Relational Analysis (GRA) for the weight loss of onions under different conditions of temperature, relative humidity, and light intensity. The table includes several key columns that show the transformation of the raw data (weight loss) through normalization and the subsequent calculation of Grey Relational Coefficients (GRC) and the Grey Relational Grade (GRG). In the first few columns, the experiment's conditions temperature (°C), relative humidity (%), and light intensity (KJ/m²) are listed for each of the nine experimental runs. The next column provides the observed weight loss (g) for each run, which serves as the basis for the subsequent calculations. The "Normalized" column represents the normalized weight loss data, which standardizes the results between 0 and 1. This step is essential in GRA to bring all factors to a comparable scale. A higher value in the "Normalized" column indicates better performance (lower weight loss). For example, the second run (temperature 20°C, relative humidity 65%, and light intensity 6 KJ/m²) has the highest normalized value of 1.000, representing the best performance (lowest weight loss), while the ninth run has a normalized value of 0.000, indicating the worst performance (highest weight loss). The "Deviation Sequence" column calculates the difference

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between the normalized values and the ideal (best) value of 1. Smaller deviations indicate better performance. For example, Run 2 has a deviation sequence of 0.000, meaning it has the best possible outcome, while Run 9 has the largest deviation sequence of 1.000, indicating the worst performance. The "GRC" (Grey Relational Coefficient) column uses the deviation sequence to compute the GRC, which ranges from 0 to 1. A higher GRC value indicates a closer relationship to the ideal performance. Run 2, with a GRC of 1.000, has the best performance, while Run 9, with a GRC of 0.333, has the worst. Finally, the "GRG" (Grey Relational Grade) is the overall score for each run, derived by averaging the GRC values. The GRG provides a single value to rank the experimental conditions. Higher GRG values indicate better overall performance. In this case, Run 2 has the highest GRG of 1.000, showing the best combination of conditions for minimizing onion weight loss, while Run 9 has the lowest GRG of 0.333, indicating the least favorable conditions. This analysis helps identify the optimal experimental conditions for minimizing weight loss based on the grey relational analysis methodology.

Table 6. Grey Relational Analysis - GRA

Run	Temperature (°C)	Relative Humidity (%)	Light Intensity (KJ/m²)	Weight Loss Mean ± SD (g)	Normalized	Deviation Sequence	GRC	GRG
1	20	60	4	5.8	0.906	0.093	0.842	0.842
2	20	65	6	5.2	1.000	0.000	1.000	1.000
3	20	70	8	6.1	0.859	0.140	0.780	0.780
4	25	60	6	7.4	0.656	0.343	0.592	0.592
5	25	65	8	6.6	0.781	0.218	0.696	0.696
6	25	70	4	8.7	0.453	0.546	0.477	0.477
7	30	60	8	9.6	0.312	0.687	0.421	0.421
8	30	65	4	8.7	0.453	0.546	0.477	0.477
9	30	70	6	11.6	0.000	1.000	0.333	0.333

Table 7 provides the ANOVA analysis for the SN ratios of the Grey Relational Grades (GRG). The analysis examines the impact of temperature, relative humidity, and light intensity on onion weight loss by determining their contribution to the overall variance. The sequential sum of squares (Seq SS) shows that temperature has the highest contribution at 83.59%, making it the most influential factor. Relative humidity contributes 15.57%, while light intensity accounts for only 0.57%, indicating a negligible effect on the outcome. The residual error is very small, at 0.25%, confirming the model's robustness in explaining the majority of the variance. The F-value column shows that temperature (326.38) and relative humidity (60.79) are statistically significant factors, with p-values of 0.003 and 0.016, respectively, both below the typical significance threshold of 0.05. Light intensity, however, is not significant, as its p-value is 0.308. The model has a very high R-squared value of 99.74%, and the adjusted R-squared of 98.98% further confirms that the model fits the data well and explains nearly all of the variability in the GRG values.

Table 7. Analysis of Variance for SN ratios of GRG

Source	DF	Seq SS	Adj SS	Adj MS	F-value	P-value	% Contribution
Temperature	2	65.6948	65.6948	32.8474	326.38	0.003	83.59
Relative Humidity	2	12.2358	12.2358	6.1179	60.79	0.016	15.57

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Source	DF	Seq SS	Adj SS	Adj MS	F-value	P-value	% Contribution
Light Intensity	2	0.45120	0.45120	0.2256	2.24	0.308	0.57
Residual Error	2	0.20130	0.20130	0.1006			0.25
Total	8	78.5831					100

S = 0.3172, R-Sq = 99.74%, R-Sq(adj) = 98.98%

Table 8 presents the response table for the Signal-to-Noise Ratios (SNR) of the Grey Relational Grades (GRG), where "larger is better." This table helps in identifying the optimal levels for each factor (temperature, relative humidity, and light intensity) in the onion weight loss experiment. For temperature, the SNR decreases as the temperature increases. At Level 1 (20°C), the SNR is -1.217, which is the highest (best), while at Level 3 (30°C), it drops to -7.832, indicating worse performance. The Delta value of 6.614 shows that temperature has the largest impact on the response, making it the most influential factor (Rank 1). For relative humidity, the highest SNR occurs at Level 2 (65%) with a value of -3.192, while the lowest SNR is at Level 3 (70%) with -6.046. The Delta value of 2.854 places relative humidity as the second most influential factor (Rank 2). For light intensity, the SNR values are relatively similar across the levels, with a slight improvement at Level 3 (8 KJ/m²) at -4.273 compared to Level 1 (4 KJ/m²) at -4.784. The small Delta value of 0.511 indicates that light intensity has the least effect on the response, and it is ranked third in terms of influence. In summary, temperature has the greatest impact on the SNR of GRG, followed by relative humidity, while light intensity has minimal influence on the outcome.

Table 8. Response Table for Signal to Noise Ratios of GRG (Larger is better)

Level	Temperature	Relative Humidity	Light Intensity
1	-1.217	-4.521	-4.784
2	-4.710	-3.192	-4.702
3	-7.832	-6.046	-4.273
Delta	6.614	2.854	0.511
Rank	1	2	3

Figure 3 presents the Main Effects Plot for SN ratios of the Grey Relational Grades (GRG), where "larger is better." The plot illustrates how temperature, relative humidity, and light intensity influence the mean SN ratios. The plot for temperature shows a sharp decline as temperature increases from 20°C to 30°C. At 20°C, the mean SN ratio is the highest, around -1, indicating the best performance. The ratio worsens significantly as the temperature rises, reaching about -8 at 30°C. This suggests that lower temperatures are more effective in minimizing weight loss, with temperature having the most substantial impact on the response. For relative humidity, the plot indicates a peak in performance at 65%, where the mean SN ratio is around -3. As humidity increases to 70%, the performance declines sharply, with the SN ratio falling to -6, showing that 65% humidity is the optimal condition for minimizing weight loss. The plot for light intensity shows minimal changes in the SN ratio across the tested levels. The values remain relatively flat, indicating that light intensity has a negligible effect on the response compared to temperature and humidity. Overall, the main effects plot confirms that temperature has the most significant influence on the outcome, followed by relative humidity, while light intensity plays a minor role.

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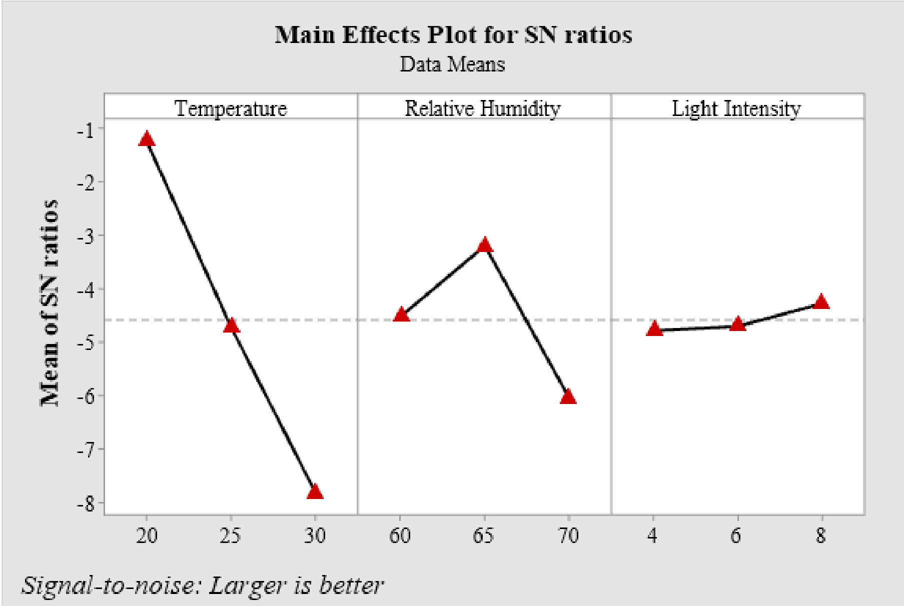

Figure 3. Main Effects Plot for SN ratios of GRG

5. DISCUSSION

The superior performance of the IoT-integrated Grey-Taguchi method in optimizing environmental control for spring onion bulb storage can be attributed to its systematic identification and maintenance of favorable conditions that minimize weight loss. This method surpasses traditional storage techniques due to its real-time monitoring and control of key environmental factors, particularly temperature and relative humidity, which significantly affect the preservation of spring onions. Through the Grey-Taguchi method, the study optimally adjusted temperature and humidity, minimizing their detrimental effects on onion weight loss. Lower temperature levels, such as 20°C, were shown to drastically reduce weight loss, as higher temperatures exacerbate physiological processes leading to degradation [3]. Relative humidity, optimized at around 65%, helped retain moisture without causing excess condensation, which could otherwise promote fungal growth or decay [4]. These optimized conditions, facilitated by the IoT system, sustained onion quality while reducing post-harvest losses an advantage especially crucial for small-scale farmers in Nakhon Phanom, where traditional methods often lack precision.

Compared to existing agricultural storage research, the IoT-based Grey Taguchi approach stands out for its efficiency in environmental control. While conventional systems address storage needs to varying extents, this method integrates advanced monitoring and control technologies to ensure consistent, optimal conditions. Previous studies, such as [1] work on crop storage systems in Southern Xinjiang, have highlighted the benefits of real-time IoT monitoring in preventing spoilage. The inclusion of the Grey-Taguchi algorithm, however, enhances the system's ability to address multi-factor challenges in storage management, proving highly effective in reducing post-harvest losses. In practical terms, this IoT-enhanced method offers small-scale farmers an accessible, automated solution for extending the shelf life of stored onions, thereby mitigating the economic losses associated with weight loss and quality degradation during storage. Traditional methods lack the same level of precision and are more vulnerable to environmental fluctuations, demonstrating the clear advantages of this innovative approach.

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6. CONCLUSION

This research addresses a critical issue faced by spring onion farmers in Nakhon Phanom: the challenge of post-harvest storage under fluctuating environmental conditions, which often results in reduced product quality, shelf life, and market value. Traditional storage methods are inadequate in maintaining the optimal environmental conditions needed for preserving spring onion bulbs, leading to substantial post-harvest losses. To address this problem, we integrated IoT technology and employed the Grey-Taguchi L9 optimization method to monitor and control key environmental factors such as temperature, relative humidity, and light intensity in real-time. The goal was to develop an effective, scalable solution that would significantly reduce storage-related losses for small-scale farmers. The methodology combined the Internet of Things (IoT) with an intelligent monitoring system, enabling real-time adjustments to environmental parameters. This system was evaluated using a Taguchi L9 orthogonal array and Grey Relational Analysis (GRA) to determine the most impactful storage conditions. Nine experimental sets were designed, varying temperature, relative humidity, and light intensity, with weight loss of the spring onions as the primary response metric. Our approach provided a data-driven solution to optimize storage conditions, thus improving product longevity.

The computational results highlighted that temperature and relative humidity had the most significant influence on reducing weight loss. Specifically, a storage temperature of 20°C and a relative humidity of 65% were identified as the optimal settings, minimizing weight loss to an average of 5.2 grams. The Grey Relational Grade (GRG) analysis supported these findings, indicating that the combination of lower temperatures and moderate humidity resulted in the best overall storage performance. Light intensity, however, was found to have a negligible effect on the weight loss of spring onions. The high R-squared value (99.74%) from the ANOVA analysis further demonstrated the robustness of the model and its ability to explain the variability in the experimental data. The key findings of this research indicate that incorporating IoT technology with optimized environmental controls can significantly enhance the post-harvest storage of spring onion bulbs. This not only benefits small-scale farmers by reducing losses but also contributes to the larger goal of sustainable agriculture. The use of IoT for real-time monitoring and adjustment of storage conditions offers an innovative and scalable solution that can be adapted to other crops and regions with similar challenges.

For future research, several areas could be explored. First, expanding the application of IoT-based environmental controls to other agricultural products could provide further validation of the methodology. Additionally, exploring more advanced IoT technologies, such as predictive analytics and machine learning, could improve the system's capability to preemptively address suboptimal storage conditions. Further research could also focus on developing cost-effective IoT systems to ensure broader adoption, particularly in rural areas with limited resources. This research presents a novel approach to agricultural storage optimization, combining IoT technology and the Grey-Taguchi method to enhance the preservation of spring onion bulbs. The findings hold significant implications for improving storage practices in agriculture, contributing to both economic and environmental sustainability.

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