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Research Article

A Novel Voltage and Air Pressure Regulator with Machine Learning for Auto-Adjusting on Bagging System

Ari Primantara[1*], Udisubakti Ciptomulyono [2], Berlian Al Kindhi[3]

[1]Interdisciplinary School of Management Technology, Institut Teknologi Sepuluh Nopember, Surabaya, 60264, Indonesia

[2]Department of Industrial and Systems Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, 60111, Indonesia

[3]Department of Electrical Automation Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, 60111, Indonesia

[*]Corresponding author: 7032222003@student.its.ac.id; Tel.: +62821-2223-0219

Abstract: This study presents the development of a machine learning-based system for regulating voltage and air pressure to automate the fertilizer bagging process. This system integrates voltage and air pressure regulator with Random Forest Regression algorithm to accurately predict the weight of fertilizer within the package and to optimize the parameters associated with the bagging process. The experiment was conducted at PT Petrokimia Gresik, using 5,000 sensor readings stored in the SCADA system, which recorded the response time of the gate valve, air pressure, and the weight of the fertilizer in the package. The findings indicate that the Random Forest Regression model, comprised of 150 decision trees, accomplishes an RMSE of 0.043 and a MAPE of 0.085%. Notably, an increase in voltage from 22V to 26V decreases response time from 40 ms to 20 ms, thereby ensuring the stability of gate valve operations. Furthermore, every additional 0.01 seconds of gate valve opening time correlates with an increase in fertilizer weight by 0.142 kg, thus highlighting the significance of voltage stability. The open-loop servo control valve system guarantees optimal air pressure during bagging. Overall, the integration of machine learning techniques and Random Forest-based control systems enhances the consistency of bagging, minimizes weight variability, and boosts production efficiency, thereby contributing to the sustainability of the fertilizer industry.

Keywords: Air pressure control; Fertilizer bagging; Machine learning; Random forest regression; Voltage regulator

1. Introduction

The fertilizer bagging process is a critical stage in the fertilizer industry that affects the quality and efficiency of production (Expósito and Velasco, 2020). At PT Petrokimia Gresik, maintaining the standardized weight of 50.2–50.4 kg is essential to minimize losses and ensure compliance (PT Petrokimia Gresik, 2023). However, achieving weight consistency remains difficult due to instability in key operational parameters. Variations in electrical voltage influence the opening and closing speed of the gate valve, while fluctuations in air pressure affect pneumatic filling performance. Even minor deviations in these variables can produce significant weight variation, increase off-spec products, and reduce production efficiency (Swamidass, 2024). Furthermore, these disturbances often occur unpredictably, making them difficult to manage using conventional manual settings or static rule-based control systems.

Advances in IoT and machine learning have enabled more adaptive, predictive control systems in industrial environments, including packaging operations (Feng et al., 2021; Allix et al., 2014). Prior research has explored sealing pressure control (Qu and Zhang, 2020), anti-interference mechanisms (Qu and Zhao, 2020), smart packaging sensors (Borghetti et al., 2022),

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and risk-based packaging systems (Fang and Deng, 2024). Other studies applied Random Forest for process optimization (Chung et al., 2024) or implemented smart pneumatic systems (Kryvoplias-Volodina, 2016). However, these works typically address isolated components and do not integrate voltage regulation, air pressure control, and machine learning in a unified, real-time framework. A comparative summary of related studies and their limitations is presented in Table 1, highlighting the absence of any approach that simultaneously controls both voltage and air pressure for fertilizer bagging.

Table 1 Comparative summary of previous studies and this study's contribution

Ref.	Focus	Limitations	This Study's Contribution
(Qu and Zhang, 2020)	Sealing pressure control in vacuum packaging	Rule-based, no ML or adaptation	Uses Random Forest to predict voltage for SOV control
(Qu and Zhao, 2020)	Anti-interference in packaging machines	No integration of real-time sensors or prediction	Combines sensor data and actuator control with ML
(Borghetti et al., 2022)	Smart sensors for food packaging	Focus on sensing, no actuator interaction	Adds actuator control based on predicted parameters
(Fang and Deng, 2024)	Risk-based packaging control system	Static logic, lacks real-time adaptiveness	Implements ML-based adaptive control loop
(Feng et al., 2021)	Secure IoT architecture	No real-world actuator implementation	Applies IoT in physical actuator control system
(Chung et al., 2024)	Parameter optimization using RF	Offline analysis, no real-time integration	Embeds RF in live SCADA-based control loop
(Allix et al., 2014)	ML model evaluation (malware detection)	Non-industrial, no physical system control	Applies RF for real-time industrial process control
(Kryvoplias-Volodina, 2016)	Proportional pressure control in packaging	Rule-based, lacks predictive modeling	Adds adaptive ML-based air pressure control for bagging precision
(Iakymchuk et al., 2014)	Pneumatic actuator for package retention	No feedback-based or ML control	Integrates ML prediction to regulate air pressure in real time
(Farahani et al., 2022)	Predictive modeling in injection molding	Focused on defect prediction, not actuator control	Integrates ML prediction directly into actuator regulation
(Zerehsaz et al., 2024)	Neural network-based control in robotic assembly	Application-specific, not generalizable to packaging systems	Applies predictive ML control to dual actuator (voltage & pressure) system in fertilizer bagging

Machine learning–based predictive control has shown success in other domains, such as injection molding (Farahani et al., 2022) and robotic assembly (Zerehsaz et al., 2024), yet these applications do not address the dual-variable, high-speed precision required for fertilizer packaging. A structured literature search covering 2010–2024 further confirmed that no prior studies integrate Random Forest Regression with actuator control for fertilizer bagging systems. This gap underscores the need for an adaptive, data-driven architecture capable of stabilizing multiple interacting variables during operation. To address this challenge, the present study proposes an integrated control system that embeds Random Forest Regression within a real-time closed-loop architecture to regulate both solenoid valve voltage and pneumatic air pressure. Using sensor inputs, gate valve response time, air pressure, and resulting fertilizer weight, the model predicts optimal actuator settings to improve consistency and reduce variability in high-speed bagging operations. The conceptual framework of the proposed system is illustrated in Supplementary 1, showing the interaction between sensors, predictive model, and actuators within a unified control loop.

In this study, the key contribution lies in the development of a Random Forest–based prediction model that is directly embedded into a real-time industrial control loop, enabling dynamic and data-driven adjustment of the bagging parameters (Chung et al., 2024). Building on this model, the research introduces a unified voltage–pressure regulation framework specifically designed for fertilizer bagging, enabling coordinated control of the solenoid valve and pneumatic system within a single architecture. Through this integration, the system demonstrates significant improvements in weight accuracy and operational stability, demonstrating how machine-learning–enabled actuator coordination can enhance the overall performance of high-speed fertilizer packaging processes. Together, these advancements present a novel and practical contribution to the growing field of smart manufacturing. Research on bagging systems has explored voltage regulation, pneumatic control, and machine-learning-based prediction, yet none has addressed their integration into a unified framework. This study introduces a coordinated control architecture in which Random Forest Regression governs both solenoid-valve voltage and pneumatic air pressure in real time to enhance stability in high-speed fertilizer bagging

2. Methods

This research was carried out in three main stages: sensor-based data collection, machine learning modeling using a Random Forest Regressor, and the configuration of the controller and actuator systems, as described below.

2.1 Data Collection Sensor

The dataset consists of 5,000 time-series records collected across three full production days in February 2025. Each day includes three shifts (07:00–15:00, 15:00–23:00, 23:00–07:00), with data sampled every 3 seconds. The sampling process reflects realistic factory conditions, accounting for operational downtime, rest periods, and occasional machine halts. This multiday sampling strategy ensures that the data captures a representative range of process variations under actual working conditions. The data is presented in Table 2.

Table 2 Sensor data for bagged products

No	Gate Valve Response Time	Air Pressure	Weight	Status
1	0.045	9.2	50.26	ONSPEC
2	0.056	9.8	50.35	ONSPEC
3	0.051	9.2	50.32	ONSPEC
4	0.057	9.0	50.30	ONSPEC
5	0.043	9.3	50.39	ONSPEC
6	0.024	9.8	50.14	OFFSPEC
7	0.023	9.9	50.08	OFFSPEC
8	0.061	8.2	50.44	OFFSPEC
9	0.022	9.8	50.06	OFFSPEC
...	...	...	...	...
5000	0.066	7.4	50.42	OFFSPEC

Table 2 presents the sample data utilized in this study. All collected data will be split into training and test sets for processing with the Random Forest algorithm. The variables consist of three predictor variables, specifically:

1. Gate Valve Response Time
   Solenoid valves regulate airflow within a gate valve system (Mercaldi et al., 2017). The response time of the gate valve is significantly affected by the electrical voltage applied to the solenoid valve (Li et al., 2024). When voltage is applied, the resulting magnetic

field either pulls or releases the valve in the solenoid, allowing for rapid and precise adjustments in valve position (Moran et al., 2024). If the voltage is unstable or unsuitable, the response time may decrease, leading to delays in airflow control (Huda and Živanović, 2017). Using voltage sensors and Random Forest Regression modeling, the system can predict and manage the optimal voltage to ensure the gate valve's response time remains within the desired range.

2. Air Pressure
   The air pressure in the bagging system must be well controlled to ensure stable, consistent product filling (Chen et al., 2024). Fluctuations in air pressure can alter product weight and reduce operational efficiency (Zhu et al., 2021). The system uses an air pressure sensor that measures pressure in real time. This data is then used in a Random Forest Regression model to predict and adjust air pressure based on historical patterns and current operational conditions. With this implementation, the system can automatically adjust the air pressure regulator to maintain pressure within a predetermined range, thereby minimizing product weight discrepancies and increasing production efficiency.

3. Weight
   Weighers or load cells ensure that the product's weight in each package meets the established standards (Arianti et al., 2021). If there is a significant deviation in weight, the system will adjust the solenoid valve voltage and air pressure to correct the error in the next bagging cycle. The product weight data collected from the load cell sensor is analyzed using the Random Forest Regression algorithm, which helps optimize operational parameters to ensure the amount of product entering the package aligns with the expected specifications. With this approach, the system can reduce off-spec products and improve accuracy in the packaging process.

The data were automatically transmitted via OPC-UA (Open Platform Communications - Unified Architecture), a secure, platform-independent standard for industrial communication. OPC-UA enabled real-time, bidirectional data exchange between the SCADA system and external servers or databases, allowing seamless sensor data acquisition and future control actions (e.g., adjusting actuator parameters). The collected data was stored in a MySQL database and exported in CSV format for further analysis. Each data record was labeled with a product quality status: ONSPEC if the bag weight was within the specified tolerance, and OFFSPEC if not. Before modeling, the dataset underwent standard preprocessing to ensure data quality and compatibility with the machine learning pipeline.

2.2 Random Forest Algorithm

Random Forest is a supervised learning method derived from Decision Trees (Malaslı et al., 2025). Unlike a single-tree model, Random Forest builds multiple trees using a bagging (bootstrap aggregation) strategy to improve prediction accuracy and reduce overfitting (Nieto et al., 2024; Breiman, 2001). Each tree is trained on randomized subsets of data and features, producing more stable and generalized predictions. Prior studies note that there is no fixed rule for determining the optimal number of trees, as model performance depends on dataset characteristics (Mary et al., 2025; Nadi and Moradi, 2019; Oshiro et al., 2012). In this study, the Random Forest Regressor (RFR) was implemented using WEKA 3.9.6. The 5,000-sample dataset underwent preprocessing that included removing records with missing values, verifying attribute ranges, detecting outliers using the IQR method, and applying min–max normalization to ensure consistent feature scaling.

After preprocessing, the dataset was deemed ready for modeling. The initial configuration used WEKA's default parameters (numIterations = 100, maxDepth = 0), allowing trees to grow fully, which increases accuracy but may increase the risk of overfitting (Chung et al., 2024). Hyperparameter tuning focused on numIterations and maxDepth by comparing RMSE, MAE, and R^2 across trials, using gate valve response time, air pressure, and bag weight as input features. Model performance was evaluated using 10-fold cross-validation to ensure robust generalization. Metrics from each fold were averaged to obtain final RMSE and R^2 values. The model was then integrated into the real-time control system to generate actuator settings. To validate reproducibility, the Random Forest model was additionally implemented using Scikit-learn 1.2.2 in a Python 3.9 environment, yielding consistent results.

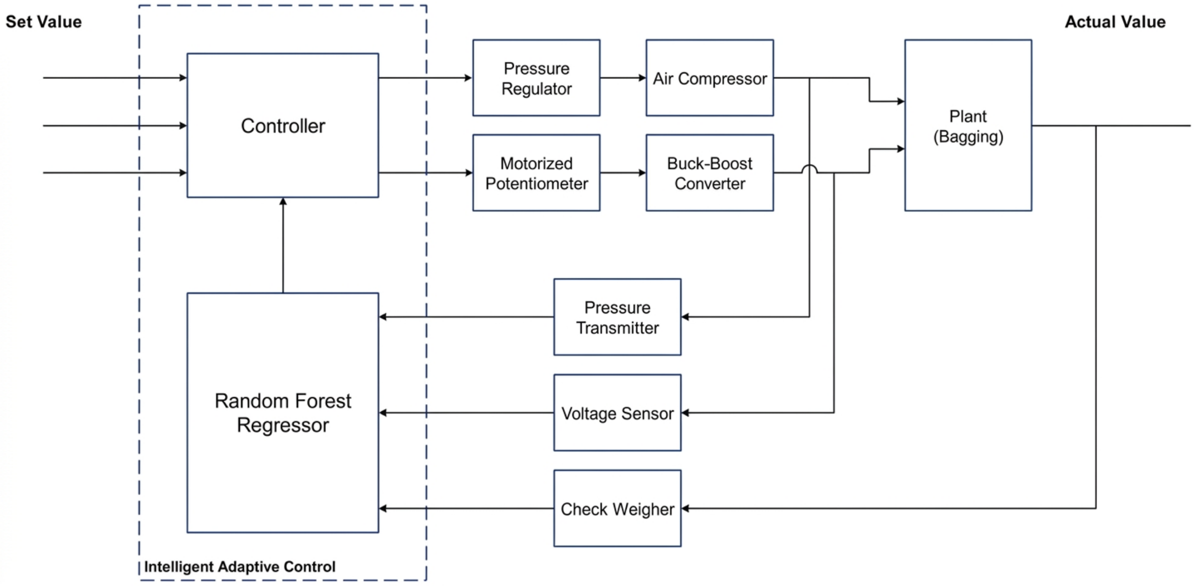

Figure 1 Block Diagram for the Bagging System

2.3 Setting Controller & Actuator

Industrial bagging systems require precise air tension and pressure control to ensure that each packaged product has the correct weight and that the process runs efficiently (Fellows, 2022). To achieve this, a controller and actuator system is used that operates automatically with Random Forest Regression. The block diagram in Figure 1 shows the architecture of the control system, comprising several main components: the Controller, Random Forest Regressor, Pressure Regulator, Motorized Potentiometer, Air Compressor, and Actuator. Each element plays a vital role in adjusting operational parameters in real time to improve efficiency and reduce bagging errors. The settings of the controller and actuator will be explained as follows:

2.3.1 Voltage Settings for Solenoid Valve (Voltage Regulator)

The Random Forest Regressor's prediction process generates data on the Response Time required to condition the Solenoid Valve. In operation, the Solenoid Valve uses electricity to energize, opening the pole on the Valve. This action occurs due to the Magnetic Field generated by the coil when voltage and current are available. In a Solenoid Valve (SOV), the relationships among voltage, current, and response time can be described by several physical equations. The voltage applied to the solenoid coil produces a current according to Ohm's Law (Parent et al., 2011) as in Equation 1:

$$V = I.R \tag{1}$$

V is the voltage (V), I_s is the current (A), and R is the coil resistance (Ω). The current flowing through the solenoid coil produces a magnetic force (F_m) that is proportional to the current. Where F_m is the magnetic force (N), k is a proportionality constant, and I_s is the solenoid current (A).

With k as a proportional constant, the greater the magnetic force, the faster the solenoid core moves, which is directly related to the response time (t_r). This response time is, in general, inversely proportional to the magnetic force. Therefore, the response time is inversely proportional to the current. Since the current I_s can be replaced by $\frac{V}{R}$ based on Ohm's Law, the relationship between response time and voltage becomes as shown in Equation (2):

$$t_r \propto \frac{1}{k \cdot V} \tag{2}$$

In equation form, the response time t_r is inversely proportional to the voltage applied to the coil. The solenoid valve used in this study is the SOV 4V310-08 type, with a power consumption of 3 W and a response time of 0.05 sec. Generally, in the field, a 24 VDC voltage is used with a fixed power of 3 W, as specified. In the analysis of the relationship between response time (t_r) and voltage (V) on the Solenoid Valve (SOV), a linear regression equation is used, which generally takes the form of Equation (3):

$$V = m \cdot t_r + c \tag{3}$$

In Equation 3, t_r represents the response time measured in seconds, while V denotes the voltage applied to the solenoid valve. The parameter m refers to the slope of the regression line, indicating the rate of change in response time for each unit change in voltage. Lastly, c is the intercept, which represents the point where the regression line intersects the t_r axis when the voltage V is equal to zero. This equation enables the calculation of the voltage required to achieve a target response time. Voltage adjustment is performed automatically using a motorized potentiometer, which modifies the PWM signal driving the Buck–Boost Converter to produce the desired output voltage. The ESP32-S3 199 controls the potentiometer through fast signal processing and I²C communication, allowing precise 200 alignment with the predicted response time. Real-time feedback is provided by the INA226 voltage–201 current sensor. Based on this feedback, the ESP32-S3 continuously adjusts the PWM duty cycle to 202 correct any deviation between the actual and target voltage, ensuring the solenoid valve maintains 203 the intended response performance.

2.3.2 Voltage Settings for Solenoid Valve (Voltage Regulator)

Stable air pressure is essential to maintain consistent bag weight in the bagging system (Primantara et al., 2024), as pressure fluctuations can cause filling inaccuracies (Chaomuang et al., 2024). Air pressure data from the sensor is processed using a Random Forest Regressor to predict the optimal pressure level, allowing the system to adjust the regulator automatically and reduce weight variability. The air compressor and servo control valve operate based on these predictions, with the ESP32-S3 modifying the PWM duty cycle to set the appropriate valve position. Real-time feedback from the pressure transmitter enables the ESP32-S3 to continuously correct deviations by adjusting the valve opening, ensuring stable airflow and maintaining the target pressure. A mathematical relationship is established between PWM duty cycle, servo rotation angle (0–180°), and output pressure (0–10 bar), forming the basis for Equation 4:

$$\theta = \frac{D}{100} \cdot 180 \tag{4}$$

Since the servo valve moves from 0° to 180°, it is possible to relate the PWM duty cycle to the valve position in degrees. Equation 5 assumes that a 0% duty cycle corresponds to a valve position of 0°, while a 100% duty cycle results in a full rotation to 180°. This relationship is used to estimate the valve opening angle (θ) based on the input PWM duty cycle (D), where θ is expressed in degrees and D in percent (0–100%). The valve's angular position, in turn, influences the resulting air pressure (P) in the system.

$$P = \frac{\theta}{180} \cdot 10 \tag{5}$$

The air pressure in the system is related to the valve position. When the valve is opened further, more air flows, increasing air pressure, and vice versa. Assuming that an angle of 0° (indicating the valve is fully closed) corresponds to a pressure of 0 bar. In comparison, an angle of 180° (indicating the valve is fully open) corresponds to a pressure of 10 bar; this allows one to identify the relationship between the resultant air pressure and the valve position. Consequently, this relationship enables converting pressure into the PWM duty cycle required to achieve the target pressure.

2.3.3 Controller and Actuator Integration

In this system, the controller serves as the central unit that regulates solenoid-valve voltage and air pressure. By integrating sensor data with Random Forest Regression, the system can adapt automatically to real-time operating conditions, improving efficiency and reducing weight variation. The predicted response time is converted into a corresponding voltage value before being applied to the motorized potentiometer, ensuring precise actuator control and stable airflow during the bagging process. Compared to Artificial Neural Networks (ANN), Random Forest requires smaller datasets and shorter training times, making it more practical for real-time use (AlShannaq and Aly, 2024; Chen et al., 2024). On the other hand, PID controllers are widely used for their simplicity and ease of implementation, but they often struggle to maintain optimal performance under varying conditions and disturbances (Kaewluan et al., 2025). In contrast, Random Forest Regression offers a robust and interpretable model that can efficiently handle complex, multi-variable systems with lower computational demands (Malaslı et al., 2025). It also adapts well to dynamic production conditions, making it a more suitable choice for real-time control in this bagging system. The integration of Random Forest Regression thus represents a novel approach that combines the advantages of machine learning and control theory to improve system performance.

3. System Components and Specifications

In this study, a variety of sensors and hardware components were integrated into the control system to ensure precise operation of the fertilizer bagging system. These components, including the load cell, pressure transmitter, motorized potentiometer, ESP32-S3 controller, and INA226 sensor, were selected based on their reliability and compatibility with the system's requirements. To ensure reproducibility, the key specifications of all components are summarized in Supplementary 2.

4. Results and Discussion

4.1 Comparison of Actual Values and Predicted Values

The testing data used in this study amounted to 5000 Data. Table 3 shows the sample data from the test results compared with the actual and predicted values. The actual value is obtained from the data, while the predicted value is computed using the Random Forest algorithm. The two values are compared to see how well the algorithm performed. Table 3 compares the predicted values for the test data with those for the training data. The table shows that the random forest model's predicted values closely align with the actual data. When the predicted values are near the actual data, the model meets the criteria for good regression (Chung et al., 2024).

Following this qualitative comparison, additional statistical metrics were calculated to assess consistency across the full dataset. The Mean Absolute Error (MAE) is 0.024, indicating minimal average deviation between predictions and actual values. The residual standard deviation of 0.030 shows low variability, while the mean residual of 0.0003 confirms the absence of systematic bias. These metrics, computed using Python and NumPy, indicate that the model provides accurate, stable, and unbiased predictions. To complement these absolute measures, relative error was also evaluated using the Mean Absolute Percentage Error (MAPE), offering a more intuitive interpretation for industrial applications.

Table 3 Comparison of actual data and predicted data

No.	Actual Value	Predicted Value
1	50.30	50.28
2	50.24	50.30
3	50.32	50.29
4	50.38	50.31
5	50.34	50.31
6	50.29	50.30
7	**50.30**	**50.30**
8	**50.28**	**50.28**
9	50.28	50.29
10	50.35	50.31

4.2 Mean Absolute Percentage Error (MAPE)

MAPE is one of the most widely used statistical methods to measure the accuracy of a model in making predictions (Ismail et al., 2020). MAPE is the absolute difference between actual data and predicted values divided by the predicted value; it will always be positive. The smaller MAPE value indicates that the model used is more accurate in making predictions (Vandeput, 2021). The random forest regression model achieves the highest predictive accuracy. The number of trees significantly affects this accuracy value, and a smaller number of trees yields a more effective prediction model. Supplementary 3 compares MAPE values across different numbers of trees. Comparing the number of trees that yield the lowest MAPE error value allows identification of the optimal tree count for building a predictive model. As shown in Table 11, the optimal number of trees that yielded the smallest error is 150 (n estimators), corresponding to a MAPE of 0.085% relative to the other tree counts. Although MAPE offers insight into percentage-based accuracy, analyzing absolute error in the original units (kilograms) is equally important. Hence, the Root Mean Square Error (RMSE) is also used as a complementary metric to assess regression quality.

4.3 Root Mean Square Error (RMSE)

The Random Forest Regression model was evaluated using Root Mean Squared Error (RMSE) to assess the magnitude of the average prediction error in the original unit (kg). RMSE is the sum of the squared errors or the difference between the actual and predicted data values (Ali et al., 2023). RMSE is widely applied to various algorithms, especially in machine learning. RMSE is based on MSE (Mean Squared Error), which is directly related to RMSE (Vandeput, 2021). A lower RMSE indicates greater model accuracy and reduced prediction error. Supplementary 4 shows the RMSE results by number of trees (nestimators). By comparing the number of trees formed to the smallest error value in RMSE, one can conclude that the RMSE value remains constant across all tree counts. This indicates that increasing the number of trees does not significantly affect the prediction error. Based on the data presented in Table 12, the model stabilizes at 150 trees, and subsequent increases in the number of trees do not markedly improve its accuracy.

4.4 Performance Analysis

Based on the performance metrics, the Random Forest model with 150 trees achieved an RMSE of 0.043, an R^2 of 0.84, and a MAPE of 0.89%, indicating high prediction accuracy and a strong fit between predicted and actual values (Kim and Kim, 2016). A 10-fold cross-validation using the same configuration yielded consistent results (R^2 = 0.84, RMSE = 0.043), demonstrating good model stability and generalizability across different data partitions. To further contextualize its effectiveness, the Random Forest approach was compared with conventional control strategies such as PID and fuzzy logic, as well as alternative machine learning models, including ANN and SVR. As summarized in Table 4, Random Forest provides higher accuracy and responsiveness while requiring less computational effort than ANN and SVR, making it a more practical and cost-efficient solution for real-time industrial control applications.

Table 4 Comparison of Control Methods: Advantages and Limitations

Method	Advantages	Limitations	References
RFR	• High accuracy ($R^2 = 0.84$) • Low computational cost • Handles non-linear relationships well • Robust to noise and outliers	• Requires large datasets for training • Longer training times for larger datasets	(Chung et al., 2024; Ma'ruf et al., 2024)
PID Controller	• Simple to implement • Well-understood and widely used • Low computational cost	• Struggles with complex, non-linear systems • Performance highly dependent on tuning parameters	(Zermani et al., 2025; Irianto et al., 2023)
Fuzzy Logic Controller	• Can handle imprecise or vague inputs • Flexible and adaptive • Good for systems with uncertainty	• Performance is sensitive to rule base design • Computationally more expensive than PID	(Yashin et al., 2025; Chekenbah et al., 2024)
ANN	• High flexibility in learning non-linear relationships • Can handle complex and dynamic systems	• High computational cost • Requires significant training data and time • Prone to overfitting without proper regularization	(AlShannaq and Aly, 2024; Amalia et al., 2023)
SVR	• Effective in high-dimensional spaces • Works well with both linear and non-linear data	• Computationally expensive • Requires fine-tuning of hyperparameters • Sensitive to the choice of kernel	(Wang et al., 2024)

The Random Forest-based control method demonstrates significant advantages over traditional control strategies and alternative machine learning models, offering a balance between high accuracy, low computational cost, and robustness. This makes it a viable solution for real-time control in industrial applications. Therefore, the Random Forest model with 150 trees can be considered an accurate and reliable tool for predicting the data, as evidenced by its low RMSE and high R^2 value. Building on this performance evaluation, the following section compares the proposed method with two widely applied control approaches in industrial settings, PID and Model Predictive Control (MPC). This comparison highlights the distinctive features of the Random Forest-based system and its relevance to dynamic, multivariable environments such as fertilizer bagging operations.

4.5 Comparative Discussion with Model-Based Control Methods

To further demonstrate the novelty and practicality of the proposed RFR-based control system, it is compared with two widely used industrial control strategies: PID and MPC. PID controllers are simple and easy to implement, but rely heavily on manual tuning and lack predictive capability, limiting their effectiveness under variable or multivariable operating conditions (Irianto et al., 2023). MPC provides predictive control through an explicit system model(Kang-Xing et al., 2025), but its implementation is computationally intensive and requires accurate modeling, which can be challenging in real-time applications (Ghiat et al., 2025). In contrast, the RFR-based approach offers a data-driven alternative that does not require a physical process model. By learning directly from sensor and actuator data, it can predict system responses and adjust voltage and air pressure in real time (Breiman, 2001).

A comparison of these three methods across key dimensions, adaptability, computational load, modeling requirements, and real-time applicability is summarized in Supplementary 5. This comparison confirms that the proposed Random Forest-based control system provides a viable and robust alternative to traditional controllers, especially in multivariable, nonlinear, and dynamic environments such as fertilizer bagging. It successfully bridges the gap between model-free simplicity and adaptive, real-time precision, making it highly suitable for deployment in modern smart manufacturing systems. To further validate the practical implementation of the proposed system, the following section focuses on empirical testing of the voltage control mechanism. Examine how variations in input voltage influence the solenoid valve's response time, a vital factor in achieving accurate material filling during the bagging process.

4.6 Performance Analysis Response Time-based Voltage Control

Tests have been conducted to prove that voltage changes have a visible effect on the Response Time in SOV. The tests were conducted at three different voltages: 22, 24, and 26 Volts, as shown in Figure 2.

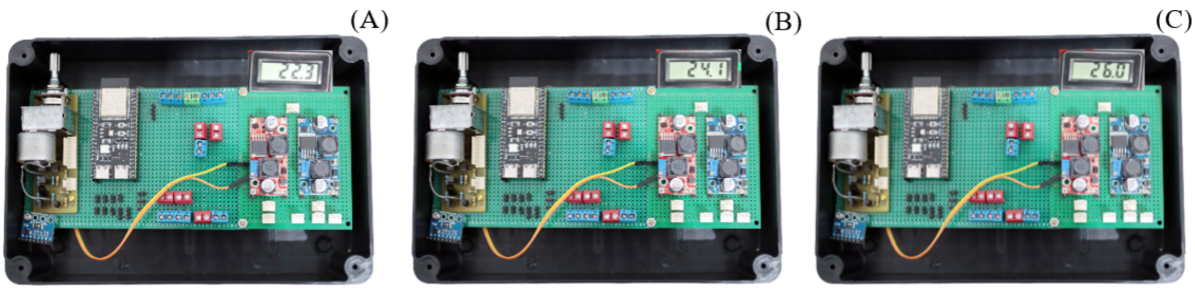

Figure 2 Testing at voltage 22 V (A), 24 V (B), 26 V (C)

Testing was conducted using the Hantek 6022BE Oscilloscope and the Hantek 6022BE Open Interface Software. The oscilloscope has a DC accuracy of ±3%, meaning its voltage measurements may deviate by up to 3% from the actual values. Additionally, the input impedance tolerance of 1 MΩ ± 1% can affect the precision of voltage measurements. For time-based measurements, such as response time, the oscilloscope's inherent uncertainty is typically ±0.1%, depending on the specific configuration. The Shunt Resistor needs to know the response time based on the current value in the coil and channel configuration done in the software. Channel 1, which is marked in yellow, indicates the form of the trigger signal from the Controller, and Channel 2, which is marked in blue, indicates the Current value from the Coil. Response Time is calculated as the time difference between the incoming trigger wave and the current value wave. The oscilloscope test results are shown in Supplementary 6 for a voltage of 22 V (A), 24 V (B), and 26 V (C).

Table 5 shows the test results for response times to different voltages. Each increase in voltage reduces the response time by 10 ms, indicating that voltage and response time are inversely proportional. In the previous SOV 4V310-08 datasheet, the response time was 0.05 seconds. However, it should be noted that the response time includes a mechanical delay factor with its own response time, in addition to the SOV coil's response time.

Table 5 Response time to various voltage test results

Voltage (V)	Response Time (ms)
22	40
24	30
26	20

Supplementary 7 presents the fitted inverse model alongside the actual data points, clearly showing the expected decrease in response time with increasing voltage. The model achieves an excellent fit, with an R^2 value of 0.9977, indicating strong agreement between the curve and measured values. Although a complete system identification or transfer-function model was not developed, this empirical relationship sufficiently captures the actuator's static behavior for control purposes. It is well-suited for real-time applications where rapid estimation is prioritized over detailed dynamic modeling. This validated relationship serves as the basis for real-time adjustment of actuator voltage to achieve consistent performance across varying conditions. Testing has been conducted based on the predicted Response Time results for the ESP32-S3. The test results are presented in Supplementary 8, which illustrates the correlation between response time and the SOV's required voltage.

The correlation test between response time and voltage was conducted using a closed-loop control system that adjusts the voltage based on the Response Time equation. This study intentionally adopts a data-driven modeling approach, avoiding formulating the bagging system as a dynamic plant using transfer functions or system identification techniques. While dynamic modeling can offer deeper theoretical insights, it is often challenging to obtain an accurate physical model in real-world industrial settings. Instead, the control method is justified based on empirical response data and statistical validation. The observed voltage-response relationship, modeled with high predictive accuracy, provides a sufficient basis for effective and adaptive control in practice. The results confirm that voltage adjustments directly affect the actuator's response time, which in turn influences the timing of the bagging system. While response time plays a critical role in control precision, the system's ultimate objective is to ensure accurate fertilizer dispensing. Therefore, the following section examines how voltage variations impact the actual fertilizer weight output, providing a comprehensive view of voltage effects across both control timing and material quantity dimensions.

4.7 Effect of Voltage on Fertilizer Weight Gain

In addition to voltage-based response-time control, the system also manages air pressure via a servo valve. This section examines the impact of voltage stability on the actual fertilizer weight gain during the bagging process. The standard urea fertilizer has a bag weight specification of

50.2–50.4 kg, as shown in Supplementary 9. The estimated filling time is approximately 3.52 seconds, based on the average gate valve opening and closing times for each 50 kg fertilizer bag (PT Petrokimia Gresik). Consequently, the filling rate can be calculated as 50 kg divided by 3.52 s, yielding a value of about 14.2 kg/s. Thus, every additional 0.01 seconds of gate valve opening can increase fertilizer weight by 0.142 kg. Supplementary 10 illustrates the impact of high voltage on fertilizer weight. This indicates that if the gate valve's opening time increases by just 0.01 seconds, it will impact the increase in fertilizer weight. These calculations reveal that voltage stability is crucial for maintaining consistent gate valve opening and closing times, thereby optimizing the fertilizer filling process in accordance with standards.

4.8 Pressure Control Using a Servo Control Valve

Air pressure in the bagging system is regulated using prediction outputs from the Random Forest model, which determine the appropriate PWM duty cycle for the servo control valve. In this configuration, the PWM duty cycle is directly proportional to the resulting air pressure: a higher duty cycle opens the valve further, increasing airflow and pressure. In comparison, a lower duty cycle reduces it. The ESP32-S3 generates the required PWM signal based on the predicted pressure value, while a pressure transmitter provides real-time feedback to maintain the desired pressure level. Operating in an open-loop arrangement, this approach enables rapid adjustment of the servo valve position and delivers stable, consistent air pressure during the bagging process.

To assess the accuracy and effectiveness of the pressure control, a validation step was conducted comparing the actual measured air pressures with the predicted pressures from the regression model. This validation involved evaluating the PWM–pressure relationship using linear regression analysis. The predictive analysis and validation metrics (RMSE and R^2) were calculated in Python on Google Colaboratory. The results demonstrated excellent model performance, as indicated by a Root Mean Square Error (RMSE) of 0.090 bar and a coefficient of determination (R^2) of 0.999. Figure 3 and Supplementary 11 illustrate the close alignment between the actual measurements and model predictions, confirming the regression model's ability to describe the PWM-based servo valve air pressure control system accurately. These results confirm the reliability and precision of the developed predictive control method for regulating air pressure in the fertilizer bagging process.

In industrial environments, operational disturbances such as pressure surges or voltage drops are common and can affect control system stability. The proposed system addresses these challenges by integrating real-time feedback. By utilizing sensor data for continuous monitoring and combining it with the Random Forest prediction model, the system can adapt to moderate fluctuations in air pressure and voltage. The model's ability to generalize over noisy or slightly varying inputs ensures that prediction and control outputs remain within acceptable thresholds. Additionally, the hardware implementation features regulated power supplies and stable pneumatic actuators to mitigate the effects of such disturbances. This design makes the system robust and resilient under dynamic operating conditions.

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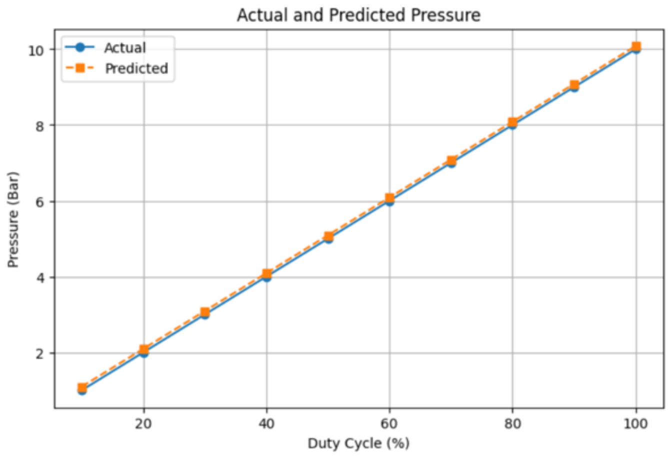

Figure 3 Comparison of actual and predicted air pressure values based on PWM Duty Cycle using a linear regression model

5. Future Work and Limitations

While the proposed system has demonstrated excellent performance in regulating voltage and air pressure through Random Forest Regression, several opportunities remain for enhancement and future research. One potential direction is to compare the current approach with other machine learning algorithms, such as XGBoost or LSTM, which may offer greater adaptability in more complex or highly dynamic environments. The experimental evaluation was conducted within a limited observation period and a specific operational context. Broader validation over extended durations and varied production conditions could further confirm the system's robustness and long-term reliability. In addition, although the control architecture currently utilizes independent feedback loops for voltage and pressure, future enhancements may explore a multivariable or adaptive control framework to better respond to interdependent fluctuations in process parameters. These future directions aim to strengthen the system's resilience and scalability, positioning it for broader adoption in innovative manufacturing environments.

6. Conclusions

This study developed a machine-learning-based voltage and air-pressure regulation system for 450 fertilizer bagging, providing a predictive control strategy that improves the accuracy and stability 451 of the packaging process. Based on 5,000 SCADA-recorded sensor data points, the Random Forest 452 Regressor achieved its best performance with 150 trees, yielding an RMSE of 0.043 and a MAPE of 453 0.085%, indicating high predictive accuracy for bag weight control. Technically, the proposed 454 voltage regulator improved the Solenoid Valve's performance by increasing the operating voltage 455 from 22 V to 26 V, reducing the valve response time from 40 ms to 20 ms. This improvement is 456 significant because even a 0.01 s increase in gate opening time can add approximately 0.142 kg to 457 the fertilizer weight, underscoring the importance of precise actuator control to maintain filling 458 accuracy. The proposed method also optimized the Servo Control Valve air pressure to support a 459 more stable bagging process and reduce process variability. Overall, the integration of machine 460 learning with voltage and air-pressure regulator control enhances packaging precision, operational 461 efficiency, and process reliability in fertilizer production, while also providing a foundation for the 462 future development of closed-loop, real-time adaptive bagging control systems.

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Author Contributions

Ari Primantara was responsible for the research design, data collection, implementation of the machine learning model, and manuscript preparation. Udisubakti Ciptomulyono and Berlian Al Kindhi supervised the research process, provided critical feedback, and contributed to refining the methodology and analysis.

Conflict of Interest

The authors declare no conflicts of interest.

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