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Simulation of a PID-Based Artificial Neural Network Controller for a Rotary Dryer in the Fertilizer Industry

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Abstract

Rotary dryers play a crucial role in the fertilizer industry by reducing the moisture content of materials after granulation. However, traditional control methods, such as Proportional-Integral-Derivative (PID) controllers, often struggle to maintain optimal performance due to dynamic changes in process conditions and manual tuning limitations. This study proposes an adaptive control system that integrates an Artificial Neural Network (ANN) with a PID controller to improve the accuracy and responsiveness of the drying process. The ANN model is designed to automatically generate optimal PID parameters (Kp, Ki, Kd) based on variations in moisture content, using a single-input (ΔM) and three-output (Kp, Ki, Kd) architecture with 10 hidden neurons. The model is trained using data obtained from MATLAB/Simulink simulations, and the training process employs the Levenberg-Marquardt backpropagation algorithm for efficient convergence. Evaluation results show that the ANN model achieves high predictive performance, with an R^2 value of 0.99868, MSE of 7.93×10^{-9}, and MAE of 5.67×10^{-5}. Transient response analysis confirms that the ANN-PID system meets industrial control standards, achieving a rise time of 28.87 ms, overshoot of 2.58%, and settling time of 0.36 seconds. The findings demonstrate that the proposed ANN-PID controller can effectively adapt to real-time moisture variations, reducing dependency on manual tuning and improving control reliability.

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INTRODUCTION

Rotary dryers are often used in the fertilizer industry for the purpose of drying materials. In most cases, the materials to be dried have undergone a granulation process prior to drying (Silvério et al., 2015). Rotary dryers are capable of removing water from materials through a heat exchange process, thereby enhancing the quality and shelf life of products such as fertilizers. The most significant advantage of rotary dryers is their capacity to process a greater quantity of material in a more efficient way than other types of dryers (Arruda et al., 2009).

However, the drying process using rotary dryers is not always as efficient as it could be due to inconsistent temperature control, often resulting from human factors or overheating. To address this issue, proportional-integral-derivative (PID) controllers were first employed for rotary dryers in 1998 and have remained the most prevalent controller type to date. However, the efficacy of PID controllers is frequently suboptimal when employed in the context of rotary dryers, due to the inherent variability in their process dynamics. Furthermore, PID parameter tuning in rotary dryers frequently lacks the capacity to adaptively accommodate changes in parameters (Somefun et al., 2021).

In this modern era, the use of artificial intelligence is a valuable tool for enhancing the functionality of control systems, such as proportional-integral-derivative (PID) controllers, thereby improving efficiency and accuracy. The application of AI to PID controllers has been widely adopted across a range of industrial sectors (Shiryayeva et al., 2024). ANN is one of the artificial intelligence algorithms that has the capacity to recognize intricate patterns and relationships between process variables through the analysis of historical data (Patel et al., 2021), thereby facilitating adaptive control. The research, entitled "Artificial Neural Network-Based Real-Time PID Controller Tuning," finds that ANN can be applied to PID control systems to predict tuning parameters that produce smaller overshoot and less settling time than the Ziegler-Nichols tuning method or the Tyreus-Luyben tuning method. This is the case even when the systems are randomly generated (Bestwick & Camarda, 2023).

The primary objective of this study is to design and evaluate an adaptive control strategy for rotary dryers by combining PID control with ANN. Unlike conventional approaches, this research emphasizes the development of a control system that can respond continuously and autonomously to changes in input, specifically in terms of moisture variation. This adaptive behavior is essential for enhancing control reliability in rotary dryer operations, particularly in dynamic industrial environments where manual tuning becomes impractical or inefficient

METHOD

Rotary Dryer System Description

Rotary dryer is the main equipment used in the fertilizer industry for drying granulated materials. A direct rotary dryer configuration is commonly applied due to its effectiveness and large capacity (Silvério et al., 2015).The configuration of the direct rotary dryer utilized in the fertilizer industry is illustrated in Figure 1.

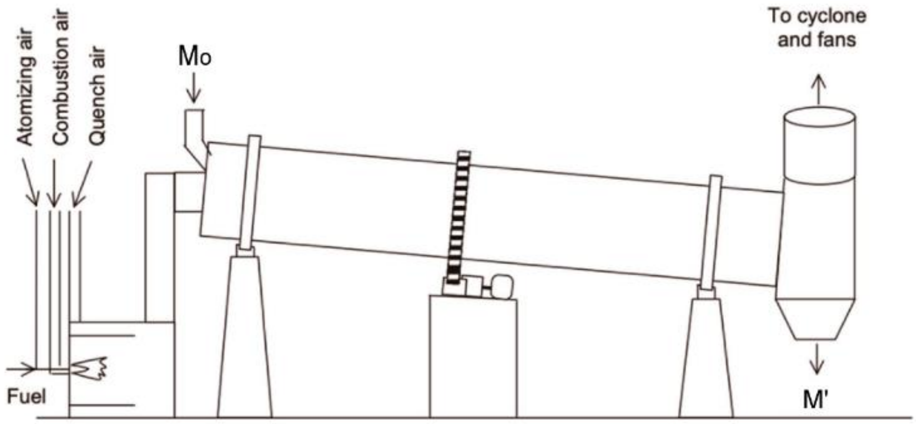

Figure 1. Rotary Dryers Machine

In this system, wet material with initial moisture content (M_0) enters from the feed end of the rotary dryer. The drum rotates continuously, allowing the material to move along the cylinder while being lifted and cascaded by a series of internal blades, which enhance the exposure of the material to the hot gas stream. During its passage through the rotary dryer, the material undergoes a drying process via heat exchange with hot air, which is generated from combustion gases. The moisture content is gradually reduced as heat is transferred from the air to the solid material through conduction and convection, occurring under near-adiabatic conditions. At the end of the process, the dried material exits the system with reduced moisture content (M'). The difference between M_0 and M' is used as a key parameter in evaluating and controlling the performance of the drying process.

The cylinder is equipped with a series of continuously rotating blades on the interior. As the drying cylinder rotates, the blades transport the material and propel it in a waterfall-like fashion into the gas stream. The retention time of the material within the drum is dependent upon the rotational speed, elevation angle, and air velocity. In a rotary dryer, the water content of the product is removed through a stream of hot air. The transfer of heat from the air to the solids results in the removal of moisture from the solids (Rubio et al., 2000).

PID Control System

Proportional-integral-derivative (PID) controller is a feedback control system that is utilized to ensure the stability and optimal performance of a given system. PID is frequently employed in rotary dryers. The PID controller operates by calculating the control signal based on the discrepancy between the desired setpoint value and the actual output value. The PID controller is comprised of three primary components: proportional (P), integral (I), and derivative (D) (Çırak & Çalık, 2023). Each component serves a distinct function. Mathematical equation of PID:

$$u_p(t) = K_p e(t) \quad \text{(Proportional)} \tag{1}$$

$$u_i(t) = \frac{K_p}{T_i}\int_0^t e(t)dt \quad \text{(Integral)} \tag{2}$$

$$u_d(t) = KpTd\frac{de(t)}{dt} \quad \text{(Derivative)} \tag{3}$$

The sum of that three:

$$u(t) = K_p\left(e(t) + \frac{1}{T_i}\int_0^t e(t)dt + T_d\frac{de(t)}{dt}\right) \quad (4)$$

$u(t) = output\ signal$
$K_p = proportional\ gain$
$T_i = integral\ time$
$T_d = derivative\ time$
$e(t) = steady - state\ error$
$K_i = integral\ gain$
$K_d = derivative\ gain$
Transfer function for PID controller:

$$U(s) = K_p + \frac{K_i}{s} + K_d s \quad (5)$$

It is necessary to fine-tune the three PID parameters in order to achieve the optimal response characteristics of the plant system. One method for determining the PID parameters is the Ziegler-Nichols approach.

Proposed ANN-PID Control System

Operational inconsistencies in rotary dryers are often attributed to manual tuning errors, which introduce delays, overshoot, and steady-state deviations (Pirrello et al., 2002). To mitigate these limitations, this study proposes an adaptive control system that integrates an Artificial Neural Network (ANN) with a Proportional-Integral-Derivative (PID) controller. This hybrid approach allows the system to automatically adjust PID parameters in response to variations in process dynamics, improving control accuracy and minimizing operator intervention.

The application of ANN to PID comprises five stages, which are as follows:

1. The objective is to determine the mathematical model of the system in order to obtain its transfer function.
2. The Block diagram is constructed to ascertain the PID parameters, specifically Kp, Ki, and Kd, of the system by modifying the transfer function and input parameters.
3. Create a dataset of SIMULINK simulation results to determine PID parameters such as Kp, Ki, Kd, and their relationship with the modeled transfer function.
4. Train the created dataset model with the target PID parameters to be integrated into the created simple system.
5. Evaluate the output of the system.

Transfer Function of Rotary Dryers

The rotary dryer operates on the technical principle of drying materials fed into it. During this drying process, there is a change in moisture content between the inlet moisture and outlet moisture. This change occurs as the machine operator adjust the temperature of hot steam used to dry materials. However, the operator may make errors in setting the rotary dryer temperature, resulting in the outlet outlet moisture deviating from the target value (Malekjani et al., 2023).

The system model developed in this paper involves installing moisture sensor to measure the inlet moisture (M_0) and the outlet moisture (M'). The difference between these moisture value is then calculated to determine the system moisture change.

$$\Delta M = M_0 - M' \quad (6)$$

Because the change in humidity 56ccurring in this system is influenced by the temperature of the tube, the second model used in this paper is to install a temperature sensor inside the rotary dryer tube to measure the temperature (T) at the inlet. In the rotary dryer system, the temperature (T) input by the operator into the machine causes a change in humidity (ΔM) over a certain period (Δt). To understand the relationship between these three parameters, a coefficient α with dimensions ($s^{-1}{}^{\circ}C^{-1}$)

is required as the gain between the two parameters. Assuming that the moisture content inside the rotary dryer changes continuously over time, the equation that can be formed is as follows:

$$\frac{dM}{dt} = \alpha T \tag{7}$$

To obtain the coefficient α that corresponds to the real-world conditions, direct experiments in the field are required, as each factory will have a different coefficient. Since this paper is based on simulation, the dataset used to form each data is also obtained from simulations using SIMULINK software. The transfer function that can be formed from the system is as follows:

$$dM = \alpha T dt \tag{8}$$

$$\int_{t_0}^{t} dM = \alpha \int_{t_0}^{t} T dt \tag{9}$$

$$M_t - M_0 = \alpha \int_{t_0}^{t} T dt \tag{10}$$

$$\Delta M = \alpha \int_{t_0}^{t} T dt \tag{11}$$

$$\mathcal{L}\left\{\Delta M = \alpha \int_{t_0}^{t} T dt\right\} \tag{12}$$

$$\mathcal{L}\{\Delta M\} = \alpha \mathcal{L}\left\{\int_{t_0}^{t} T dt\right\} \tag{13}$$

$$\Delta M(s) = \frac{\alpha}{s} T(s) \tag{14}$$

$$\frac{\Delta M(s)}{T(s)} = G(s) = \frac{\alpha}{s} \tag{15}$$

Train and Evaluate the Model of ANN

This section will explain the process of creating an ANN model to obtain the optimal PID parameters (Kp, Ki, Kd) for the system.

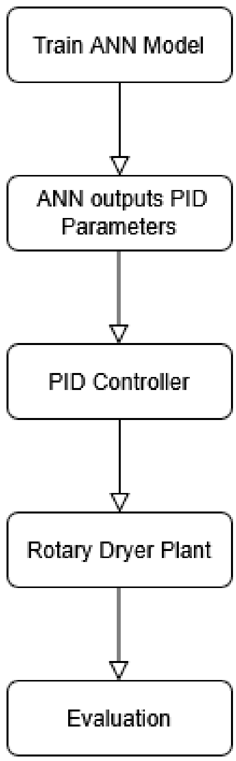

Figure 2. Flowchart of ANN-PID system

Data Collection

In this study, a dataset consisting of 20 samples was constructed to support the training and evaluation of the ANN-based PID tuning model. The input variables were the inlet moisture (M_0) and final moisture (M'), which reflect the operational characteristics of rotary dryers. These values were referenced from empirical studies in literature on fertilizer drying systems (Friso, 2023) , as well as from synthetic data derived via Simulink-based simulation of typical dryer behavior under varying thermal loads.

To generate the target outputs for ANN training, the rotary dryer process was modeled in MATLAB/Simulink using a conventional PID control block. The Simulink PID autotuner was employed to identify optimal controller gains (Kp, Ki, and Kd) for each moisture variation scenario. Each tuning scenario was configured to minimize rise time, overshoot, and settling time, with parameters automatically adjusted until the system response met stability and performance thresholds.

The final dataset comprises pairs of moisture characteristics (ΔM $=M_0-$ M') as input features and the corresponding PID parameters (Kp, Ki, Kd) as output labels. These samples represent the core knowledge base used to train the ANN, enabling it to learn the functional mapping between moisture variation and optimal controller settings.

All simulations were conducted under steady-state assumptions and constant ambient drying conditions to ensure comparability between samples. The data generation and PID tuning process was fully automated and repeatable to support reproducibility of results.

Data Preprocessing

The collected data is processed to ensure its quality and suitability for the PID tuning process. One of the steps in data preprocessing is data normalization using MinMaxScaler, which is a feature scaling technique in machine learning (C R & C P, 2024).

$$Xscaled = \frac{X-Xmin}{Xmax-Xmin} \tag{16}$$

Data Splitting

The dataset containing inlet moisture, final moisture, and target PID parameters (Kp, Ki, Kd) is divided into three parts: 70% for training data, 15% for testing data, and 15% for validation data. This division aims to ensure that the performance of the backpropagation algorithm can be evaluated objectively. From a total of 20 data samples, this results in 14 data for training, 3 data for testing, and 3 data for validation.

Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a type of computational model inspired by the workings of biological neural networks in the human brain. The working process of ANN involves learning patterns from data by adjusting the weights and biases of each neuron during training (Walczak & Cerpa, 2003).

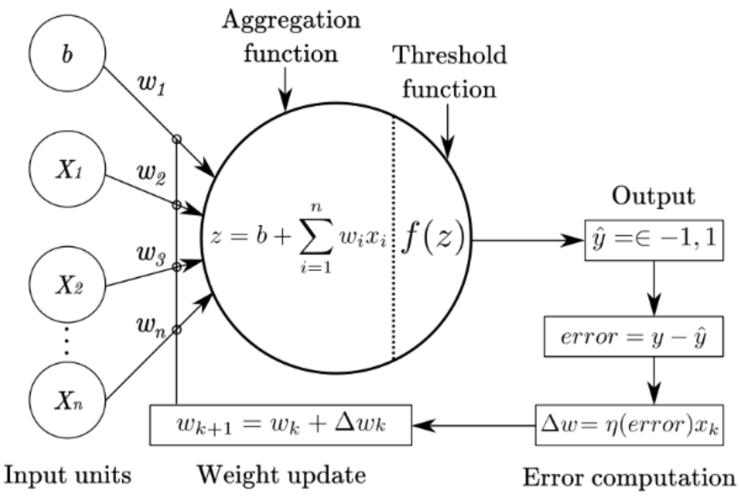

Figure 3. Model of ANN

The ANN training in this study will use backpropagation. Backpropagation is an algorithm used to train ANN by updating weights based on the error between the predicted results and the target values (Ren & Wang, 2023) . This algorithm employs the gradient descent method to minimize the loss function. The backpropagation process consists of three main steps:

1. **Forward Propagation**: Input data is calculated as it passes through the network to produce predictions.
2. **Backward Propagation**: The gradient of the loss function is calculated with respect to the network's weights using the chain rule.
3. **Weight Update**: Weights are updated to minimize prediction errors.

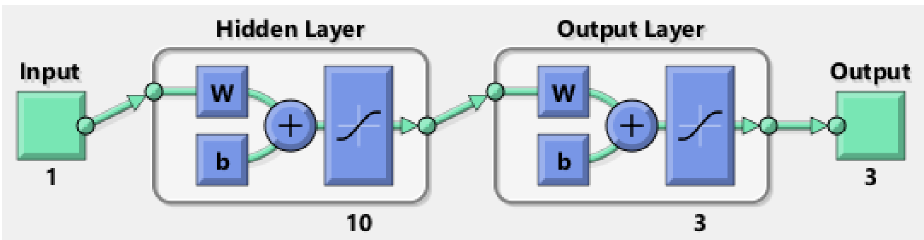

Figure 4. Architecture of proposed ANN

The network architecture includes a single hidden layer with 10 neurons, which is a widely accepted configuration for regression tasks in Artificial Neural Networks. This structure offers a good balance between model complexity and computational efficiency, particularly in simulation-based studies.

Table 1. Architecture of proposed ANN

Network Type	Backpropagation
Training Function	Levenbert Marquard (trainlm)
Adaption Learning Function	Learngdm
Performance Function	Mean Squared Error (MSE)
Transfer Function	Tansig
Input Data	ΔM (The difference between the initial moisture Mo and the final moisture M’)

Output Data	Kp, Ki, Kd (the PID control gains)
Hidden Layer	10
Amount of data	20

The Artificial Neural Network (ANN) designed in this study is a single-input and three-output model trained using the backpropagation algorithm with the Levenberg-Marquardt (trainlm) optimization method. This algorithm is chosen due to its fast convergence properties, which are particularly advantageous for small to medium-sized datasets (Yan et al., 2021). The adaptation learning function used is learngdm (gradient descent with momentum), and the performance function is the Mean Squared Error (MSE), which measures how closely the predicted PID parameters align with the target values. The transfer function for the hidden layer is tansig (hyperbolic tangent sigmoid), which introduces nonlinearity into the network, allowing it to approximate complex functions.

In this research, the dataset consists of 20 samples used for training, validation, and testing. While relatively small in the context of large-scale machine learning applications, this dataset size is appropriate for a proof-of-concept study aimed at demonstrating the feasibility of an adaptive control strategy. Moreover, with careful data preprocessing and the application of a well-established training algorithm (Levenberg-Marquardt), meaningful insights can still be obtained

The difference between the initial moisture Mo and the final moisture M', denoted as ΔM, is utilized as the input feature. This is because ΔM represents the primary indicator of the drying process performance, reflecting how effectively the rotary dryer removes moisture from the material. It directly correlates with temperature control and system dynamics, making it a suitable variable for the ANN to learn the pattern that determines optimal PID gains (Kp, Ki, Kd).

Model Evaluation

The performance evaluation of the ANN-PID control model is conducted using three key error metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2). MSE quantifies the average squared difference between the system output and the reference values, where a lower MSE signifies the model's effectiveness in minimizing large deviations. MAE, on the other hand, measures the average magnitude of absolute errors, providing an intuitive assessment of prediction accuracy in the same units as the output variable. The R^2 value assesses how well the ANN-PID model accounts for the variability in the system output, with a value approaching 1 indicating a strong correlation between the predicted and reference values, thus demonstrating the model's capability to accurately follow the desired behavior of the rotary dryer system.

Table 2. Minimum Criteria Of System

Parameter	**Value**
Rise Time	<50 ms
Overshoot	<10%
Undershoot	<5%

As part of the evaluation of the proposed ANN-PID system, we adopted evaluation criteria from the work of Stewart & Davison (2006)., which set optimal transient performance standards for PID-based control systems to ensure the reliability and stability of the control system in industrial applications. The implemented evaluation parameters include rise time (<50 ms), which is the time required for the system to reach 90% of the steady-state value after a change in input, ensuring a quick and accurate response; overshoot (<10%), the maximum percentage by which the system output exceeds the desired steady-state value, minimizing the risk of instability or material degradation due to temperature fluctuations; and undershoot (<5%), the maximum percentage by which the system output drops below the steady-state value during the transient phase, ensuring stable temperature control throughout the drying process. These criteria were measured using MATLAB simulation tools, including the Bilevel Measurements feature, to evaluate rise time, overshoot, and undershoot under various operational conditions, guaranteeing that the proposed ANN-PID system meets the high-performance standards required in industrial applications.

Integrate ANN Model and Evaluate Performance to System

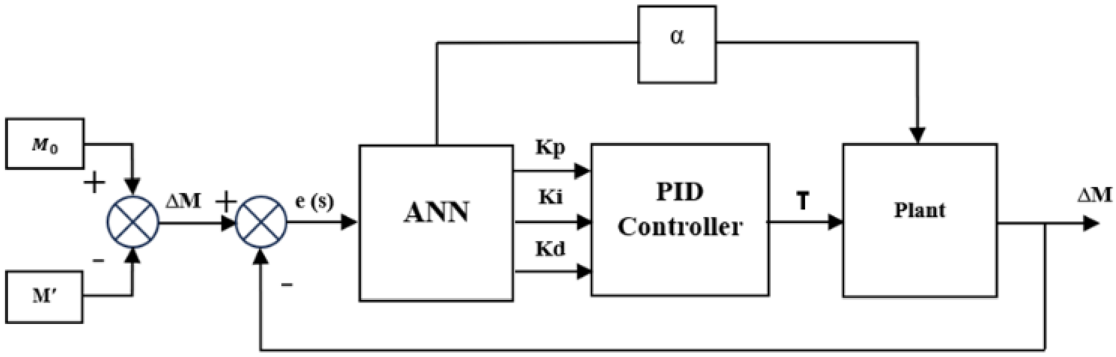

Figure 5. System Block Diagram

The diagram in igure 5 illustrated the system. The error e(s) calculated from the difference between the initial moisture content (M_0) and the desired final moisture content (M'), which is then fed into the ANN. The ANN dynamically adjusts the PID parameters (Kp, Ki, Kd) based on this error, allowing the PID controller to optimally regulate the drying temperature (T). This temperature is applied to the plant (rotary dryer), resulting in a moisture change (ΔM) that is fed back into the system for continuous adjustment. A coefficient α is used to model the relationship between temperature and the rate of moisture change

RESULTS AND DISCUSSION

This section presents the evaluation results of the ANN-PID control model based on simulation outputs. The performance of the proposed system was assessed using standard error metrics and transient response characteristics. The evaluation focuses on both the predictive accuracy of the ANN model in estimating PID parameters and the effectiveness of the integrated control system in regulating moisture content in the rotary dryer process.

Performance of the ANN

The regression plots illustrate the performance of the Artificial Neural Network (ANN) model in predicting PID parameters based on input data during the training, validation, testing, and overall evaluation stages. The correlation coefficients (R) obtained are 0.99991 for training, 0.99734 for validation, 0.99677 for testing, and 0.99868 for the overall dataset. These high R values across all phases indicate that the model demonstrates excellent predictive accuracy and consistently captures the underlying relationship between input and output. The regression lines closely follow the ideal line, signifying that the differences between predicted and target values are minimal. These results confirm that the ANN model not only fits the training data well but also generalizes effectively to unseen data.

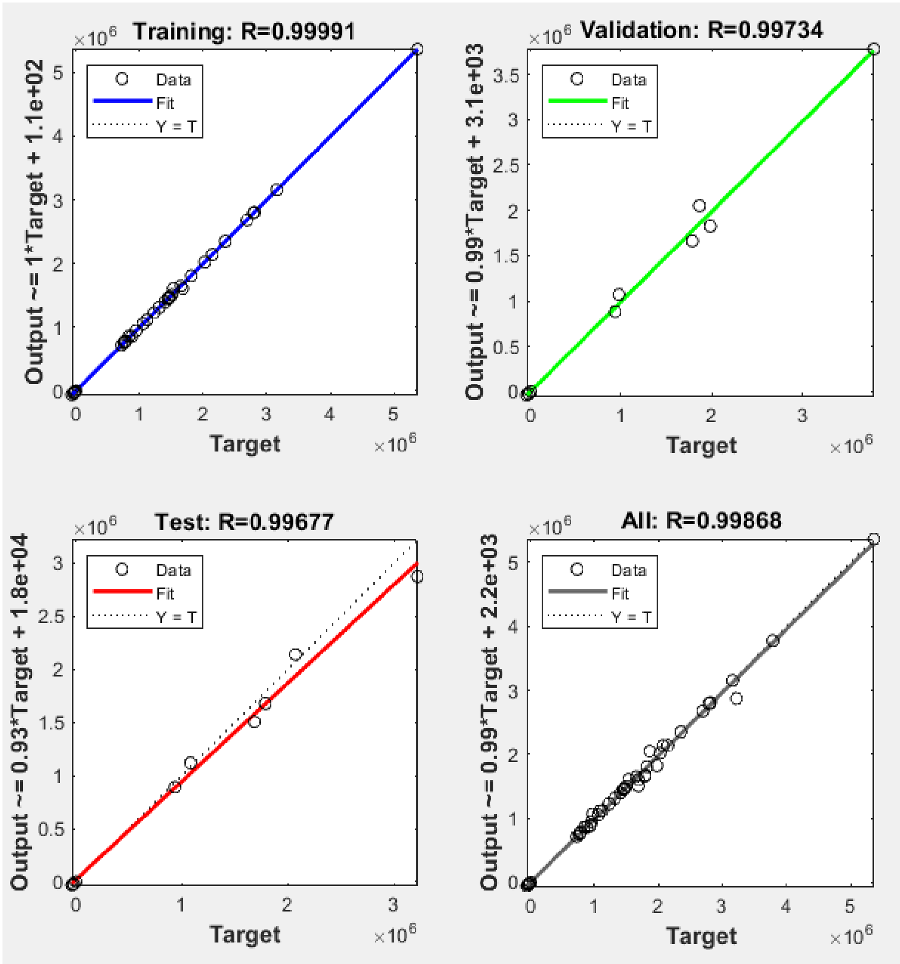

Figure 6. Regression

Performance of The Simulation Model

Table 3. Minimum Criteria Of System

No	Inlet Moisture	Final Moisture	ΔM Input	ΔM Output Simulation	Error (ΔM Input - ΔM Output)
1	0.387	0.142	0.245	0.24508	0.00008
2	0.4	0.1	0.3	0.3	0
3	0.602	0.132	0.47	0.46998	0.00002
4	0.723	0.133	0.59	0.59002	0.00002
5	0.7	0.1	0.6	0.60002	0.00002
6	0.893	0.124	0.769	0.7688	0.0002

To test the performance of the developed system, simulations will be conducted using MATLAB with 6 different inputs.

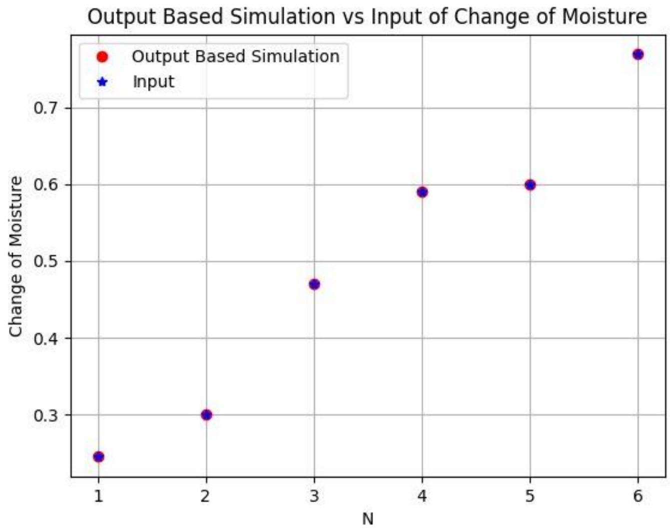

Figure 7. Comparation Value

The comparison between the input moisture change (ΔM Input) and the simulated output (ΔM Output Simulation) is summarized in Table 3 and visualized in Figure 7. The error between the input and output is minimal across all test cases, indicating a strong agreement between the expected and actual system behavior.

Quantitatively, the simulation model achieved a Mean Squared Error (MSE) of 7.93333×10^{-9}, which reflects the average squared difference between the input and the predicted output. In addition, the Mean Absolute Error (MAE) was 5.66667×10^{-5}, representing the average magnitude of the absolute errors. These values confirm that the developed system is highly accurate and stable under various operating conditions.

The graph in Fig. 8 further validates the result, showing that the output values (red) almost perfectly overlap with the input values (blue) for all six simulation scenarios. The high level of agreement, low error metrics, and visual conformity together demonstrate the effectiveness of the ANN-PID model in predicting and controlling the rotary dryer system with minimal deviation.

To further assess the dynamic behavior of the rotary dryer system under the proposed ANN-PID control, a transient response analysis was conducted using the MATLAB Bilevel Measurements tool. The key performance indicators recorded include a rise time of 28.873 ms, indicating the system's ability to respond rapidly to input changes, and an overshoot of 2.577%, suggesting the system maintains control stability with minimal excess response. Additionally, the system exhibited a slight undershoot of -0.778%, which reflects a brief drop below the steady-state value due to initial compensatory behavior. The settling time was recorded at 0.3605 seconds, demonstrating that the system quickly stabilizes after disturbances. Furthermore, the slew rate was measured at 6.817 1/s, indicating a balanced rate of signal change that ensures responsiveness without abrupt fluctuations. These results confirm that the ANN-PID controlled system delivers a stable transient response, with minimal overshoot and undershoot which is essential characteristic in thermal control applications such as rotary dryers, where excessive temperature deviation could degrade material quality.

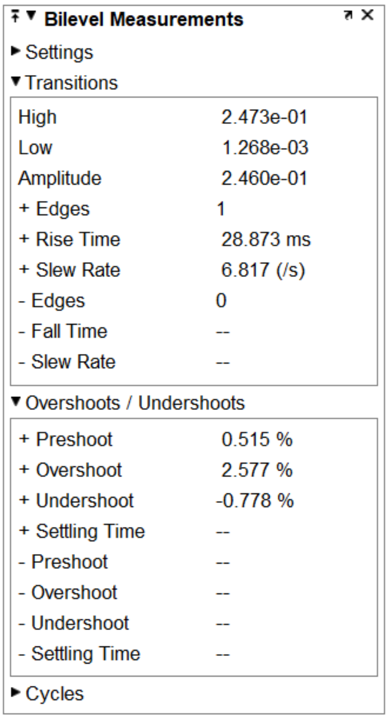

Figure 8. Bilevel Measurement

CONCLUSION

Based on the ANN-PID model simulation results and transient response analysis, it can be concluded that the developed control system is capable of responding to continuous changes in moisture input with both speed and stability. The obtained Mean Squared Error (MSE) of 7.93333×10^{-9} and Mean Absolute Error (MAE) of 5.66667×10^{-5} indicate that the model's predictions are highly accurate compared to the target values.

From the transient response perspective, the system achieved a rise time of 28.873 ms, overshoot of 2.577%, and settling time of 0.3605 seconds. These results are all well within the system's minimum performance criteria that need a rise time of less than 50 ms, overshoot under 10%, and undershoot under 5%. This confirms that the system can quickly adapt to input changes with minimal deviation, ensuring stable and efficient operation.

Therefore, the primary objective of this research has been successfully achieved: to develop an adaptive ANN-PID control system capable of real-time response to continuous input variations. The system effectively eliminates reliance on manual tuning, which is prone to human error and not suitable for dynamic operating environments.

It is important to note that this study does not aim to optimize energy efficiency, reduce operational costs, or evaluate economic performance, as those aspects were beyond the scope of this research.

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