SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I5P114

Volume 12 Issue 5, 162-170, May 2025
© 2025 Seventh Sense Research Group®

Original Article

Optimization of Temperature Control in Extrusion Machines Using Machine Learning Algorithms

Wilber Catachura Titi[1], Michael Ruben Ccala Achahuanco[2], Jesus Talavera Suarez[3]

[1,2,3]*Universidad Nacional de San Agustin de Arequipa, Arequipa, Perú.*

[1]*Corresponding Author : wcatachura@unsa.edu.pe*

Received: 09 March 2025 Revised: 12 April 2025 Accepted: 13 May 2025 Published: 27 May 2025

Abstract *- Extrusion machines require precise temperature control to maximize energy savings during manufacturing processes and ensure product quality. This paper presents a new Machine Learning (ML) based strategy for optimizing temperature regulation in real-time. The suggested method learns the behavior patterns of extrusion machines under various operating settings and then dynamically adjusts the stress and temperature parameters to achieve faster and more accurate management. The models and experiments demonstrate a notable reduction in temperature fluctuations and a notable improvement in energy consumption when compared to traditional control methods. Additionally, by employing machine learning, any irregularities in the process may be anticipated, enhancing the system's long-term stability and functionality. This method offers a flexible and effective way to regulate temperature in industrial settings, which might revolutionize extrusion operations.*

Keywords *- Temperature control, Machine Learning, Extruder machines, Process optimization.*

1. Introduction

In the industrial sector, precise temperature control in extruders is essential to ensure product quality, operational efficiency, and the reduction of waste that delays material production. Extruders, used in various industries, such as food, metallurgy, and polymer manufacturing, depend on effective thermal management to preserve the qualities of the material they process and thus avoid excessive losses in the industry [1]. Temperature fluctuations during the extrusion process can lead to undesirable changes in the mechanical and chemical qualities of the final product, uneven material distribution or thermal deterioration [2, 3]. Conventional temperature control techniques, such as those based on PID (proportional-integral-derivative) systems, provide reliable results but are not flexible enough to react quickly to changing operating conditions [4]. Although fuzzy logic and advanced predictive control systems have advanced considerably, small and medium-sized companies have not been able to adopt these technologies due to their high implementation costs and complexity [5, 6].

Considering the use of Machine Learning (ML) techniques shows promise. Automatically modifying system settings in response to temperature changes the system will experience can provide more efficient and adaptable control [7, 8]. Integrating real-time data from several sensors and their advanced features to optimize thermal stability and conserve energy is another benefit of machine learning, which boosts the economy and shields the environment from potential contamination [9]. Creating and applying a temperature control system based on machine learning algorithms for extruder machines is necessary to improve the stability of temperature control, reduce response times and increase the energy efficiency of the process [10-12].

This study proposes designing and implementing a Machine Learning (ML)-based temperature management system for extrusion machines. By offering an adaptive solution that can instantly respond to temperature changes and changing circumstances throughout the extrusion process, the system is designed to address the disadvantages of traditional control techniques, such as Proportional-Integrative-Derivative (PID) systems. Furthermore, the system collects historical and current temperature and other data from electronic sensors located along the extruder barrel used for system validation. This data includes operational variables such as feed rate, material viscosity, and environmental parameters (including the previously obtained temperature parameter). After processing, the pre-trained supervised learning algorithm searches for patterns in the system dynamics. It generates predictive models that automatically adjust the extruder supply voltage settings to maintain optimal thermal stability and anticipate thermal deviations. Finally, a simulation framework is incorporated to test various algorithm configurations and evaluate their performance under various conditions, such as sudden changes in feed rate or material composition. This approach can potentially improve the trained model and test it in various situations that may arise.

This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/)

The rest of the document is structured as follows: Section 2 presents the works related to the research. Section 3 presents the methodology used to perform the data acquisition. Section 4 presents the experimental development used for the classification of sleepiness. Section 5 shows the results obtained and their respective discussion. Finally, Section 6 contains the conclusions and the projection of future work.

2. Related Works

Research on temperature regulation in industrial processes using state-of-the-art technology, such as adaptive control systems and machine learning algorithms, has increased significantly in recent years. Based on a new focus on integrating novel techniques and heat management in extrusion machines, this part reviews the most relevant recent research addressing the challenges associated with the current topic. In the paper by Oskolkov et al. [13], a thermal control approach in extrusion-based on high-frequency induction heating combined with resonant temperature measurement was proposed. This method reduced thermal control errors from 20 °C to 0.2 °C, in addition to significantly decreasing response times. This study clarified how crucial it is to use precise measurement and control methods to raise product calibre and consistency.

Conversely, Anderegg et al.'s study [14] looked at how extrusion-based additive manufacturing, which allows for the sequential addition of material layers to form Three-Dimensional (3D) objects, may be integrated with in situ monitoring devices. This method controlled internal process conditions dynamically using temperature and pressure sensors. This study also shows how real-time monitoring can greatly minimize temperature variations, improve the mechanical qualities of the final product, and open the door for modification of the extrusion system [14]. Another research by Abeykoon et al. [5] included a thorough analysis of energy efficiency in polymer extrusion processes and established the relationship between energy consumption and material rheological properties. In order to maximize thermal stability without sacrificing energy efficiency, this study also emphasized the necessity of adjusting processing parameters and investigating novel technologies challenge that the current work attempts to solve.

Ren et al., in their 2017 paper [15], proposed a model for parameter optimization in extrusion-based 3D printing using polymers and binders, i.e., they applied a substance that allowed the polymers to stay together. This approach included real-time adjustments of temperature and flow rate, also demonstrating how thermal variations directly influence the structural quality of printed products. The insights found as a result of their research are relevant to traditional extrusion, even if their application focused on additive manufacturing. Han et al. [16] investigated the application of electrochemical extrusion for liquid metal processing in a different paper. A notion also investigated in this study is to improve temperature management in extrusion machines. This work demonstrated the potential of adaptive control systems to maintain ideal conditions in extremely dynamic processes. Despite all the advances that exist today in 3D printing, there is still a gap in the specific integration of machine learning algorithms for temperature control in industrial extruders. While some work has demonstrated the positive impact of advanced technologies in manufacturing, few have explored how learning systems can offer a practical and cost-effective solution for traditional industrial applications. This study attempts to fill this gap by proposing a system that leverages the capability of machine learning algorithms to improve thermal accuracy and stability while reducing energy and operating costs.

3. Methodology

The methodology of this study focuses on the design, implementation and validation of a temperature control system for extruder machines using machine learning (ML) algorithms. An approach based on historical and real-time data analysis is developed to adjust the voltage parameters dynamically, thus optimizing the thermal stability of the extrusion process. The methodology is divided into four main stages: data acquisition, model preprocessing and training, control system implementation, and experimental validation. Figure 1 shows the flow diagram of the proposed complete system.

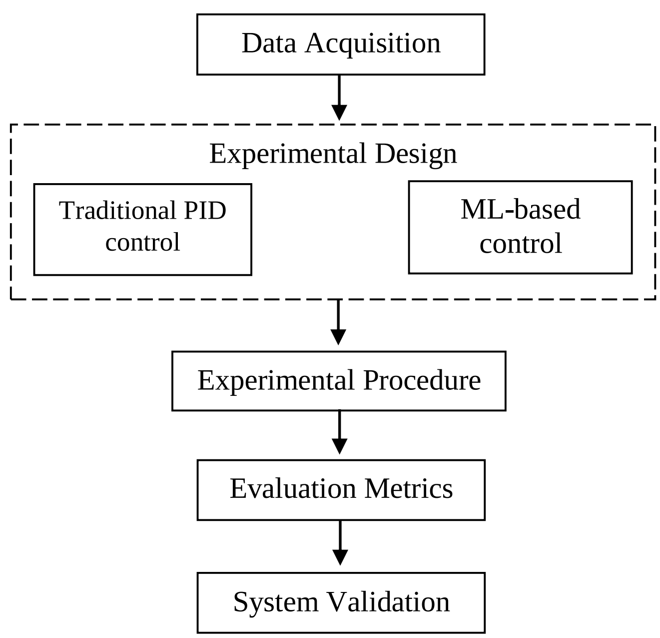

Fig. 1 Flow diagram of the proposed system

3.1. Data Acquisition

The temperature control system for this experiment was developed and tested using a single-screw extruder fitted with a resistive heating system. This configuration made it possible to monitor and control the temperature precisely during the extrusion operation. Type K thermocouples were positioned at various locations along the extrusion barrel to provide precise temperature readings. Real-time temperature measurements from these sensors, renowned for their reliability and accuracy of ±1 °C, were crucial to maintain stability throughout the procedure. The central processing unit, the ESP32 microcontroller, was responsible for collecting the thermocouple data and running the machine-learning algorithms. This microcontroller was ideally suited to manage the control system efficiently thanks to its low power consumption. It integrated Wi-Fi connectivity for real-time applications, which is necessary for this proposed system. The voltage was controlled by a TRIAC module integrated into the developed system. This microcontroller was ideally suited to manage the control system efficiently, thanks to its low power consumption and integrated Wi-Fi connectivity for real-time applications, which is necessary for this proposed system. The voltage was controlled by a TRIAC module integrated into the developed system. This module, which was controlled by the ESP32, allowed for accurate temperature control by adjusting the current supplied to the heating components. This approach made switching more seamless compared with conventional on/off control techniques by decreasing fluctuations and boosting overall stability. The experiment's test extruder, which has a 2 KW heating capability, was made to produce thermoplastic polymers. This configuration allowed the suggested temperature control technology to be accurately evaluated in real-world applications, as it closely resembled the current working environments in which this system might be used. Figure 2 shows the block diagram of the electronic circuit used to obtain and display the results.

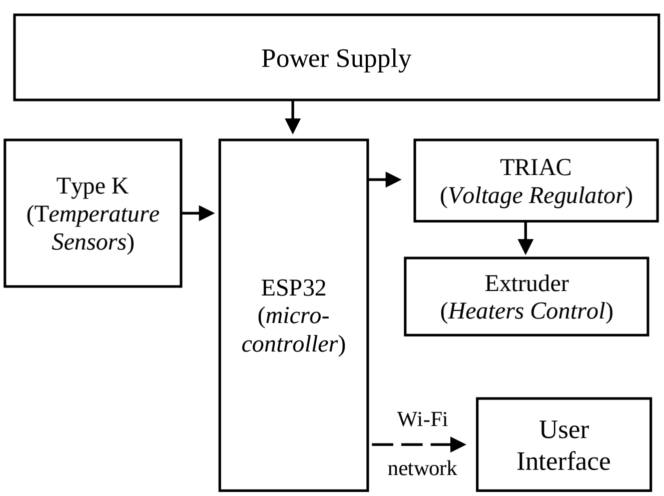

Fig. 2 Electronic circuit block diagram

3.2. Experimental Design

The experiment consisted of operating the extruder under different load conditions and evaluating the performance of the thermal control in two configurations:

- *Traditional PID control*: Adjusted with optimum gain values (K_p, K_i, K_d) obtained by calibration.
- *ML-based control*: Using a Random Forest model pre-trained with historical and real-time data to predict optimal voltage settings.

For each configuration, thermal stability tests were performed, where the barrel temperature was to be maintained in a target range of 230°C to 250°C, typical in polymer extrusion processes. Temperature measurements were recorded every second for a period of 60 minutes, allowing analysis of variations and the ability of the system to adapt to external disturbances, such as changes in feed rate or environmental variations.

3.3. Experimental Procedure

Temperature sensors were positioned at three key locations on the extruder barrel as part of the experiment. These sensors were linked to an ESP32 microprocessor to gather data in real-time. The sensors were calibrated by contrasting their readings with a reference thermometer to guarantee measurement accuracy. Using tools such as TensorFlow, machine learning models were developed and trained in Python. By anticipating temperature changes and adjusting power levels accordingly, these technologies enabled the creation of predictive algorithms that optimized the extruder heating process and significantly increased system efficiency, achieving better results than with basic on-off control.

A Random Forest model was developed to predict the ideal voltage setting based on the current temperature and its thermal tendency during the training phase of the machine learning model proposed in this system development by collecting operational data over multiple sessions. The performance of the machine learning-based system and the Predictive, Integrative, and Derivative (PID) control were independently evaluated in a controlled test conducted on the extruder to provide a baseline. A thorough comparison of the results was performed to assess the effectiveness of the machine learning-based control system compared to the traditional PID technique, paying special attention to crucial performance metrics such as thermal stability, reaction time, and energy consumption. This comparison was necessary to verify the effectiveness of the proposed system against other traditional systems found in the literature.

3.4. Evaluation Metrics

To quantify the effectiveness of the thermal control, the following metrics were used: The Mean Square Error (MSE) is found by applying Equation (1):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(T_i - T_{objetivo}\right)^2 \qquad (1)$$

Where T_i is the temperature recorded at instant i and $T_{objetivo}$ is the desired temperature.

Three main metrics were used to evaluate the system's success. Initially, stabilization time calculations were performed, which determined the time required to stabilize the system at a desired temperature of ±2°C. Secondly, the difference between the maximum and minimum peak temperatures observed during the operation was used to determine the thermal drift. Finally, to analyze the effectiveness of the system's energy optimization, energy efficiency was assessed by monitoring total power consumption during each test.

3.5. System Validation

Tests are conducted using a laboratory extruder in a controlled setting to assess the system's performance. Metrics like thermal stability, reaction time, and energy usage are measured by comparing the temperatures acquired with the ML system to a conventional PID control. The data are examined using statistical methods to ascertain the suggested strategy's efficacy.

4. Experimental Development

The experimental development was carried out to evaluate the performance of a Machine Learning (ML) based temperature control system compared to a traditional PID control system on a laboratory extruder machine. This section describes the materials and equipment used, the experimental design, the procedures implemented, and the evaluation metrics used to analyze the effectiveness of the proposed system.

4.1. Data Acquisition

Temperature sensors positioned along the extruder barrel provide real-time data used to build the control system. Type K thermocouples are employed due to their rapid reaction and broad measuring range. Additionally, operational factors are documented, including feed rate and voltage delivered to the heating components. Data samples are taken every one second and saved in a database for further modeling and analysis.

4.1.1. Temperature Sensors

K-type thermocouples, which were chosen for their broad measuring range (-200°C to 1300°C), thermal stability, and quick reaction to temperature changes, were utilized for temperature monitoring along the extruder barrel. Three sensors were installed at strategic points along the extruder barrel to ensure accurate thermal monitoring throughout the process. The initial entrance temperature is recorded by the first sensor, which is situated in the feed zone, prior to the material being passed through the screw. The second sensor is in the compression zone and detects the temperature as the material is melted and compacted inside the extrusion chamber. In the dosing zone, the third sensor detects the temperature right before the material leaves the nozzle to ensure extrusion occurs under ideal thermal conditions. Every K-type thermocouple has a digital output compatible with the ESP32 and a signal amplifier (MAX6675).

The MAX6675 converts the millivolt signal generated by the thermocouple into an accurate temperature reading via Serial Peripheral Interface (SPI), ensuring stable, interference-free communication; SPI communication allows the ESP32 to receive real-time data from the sensors and process it to adjust the voltage applied to the heaters dynamically. Each MAX6675 was connected to the ESP32 via the following pins: VCC to 3.3V of the ESP32, GND to GND of the ESP32, Serial Clock (SCK) to GPIO18 of the ESP32, Chip Select (CS) to GPIO5 of the ESP32 (for the first thermocouple), GPIO17 (for the second) and GPIO16 (for the third), Serial Output (SO) to GPIO19 of the ESP32. In Figure 3, you can see all the connections that were previously explained.

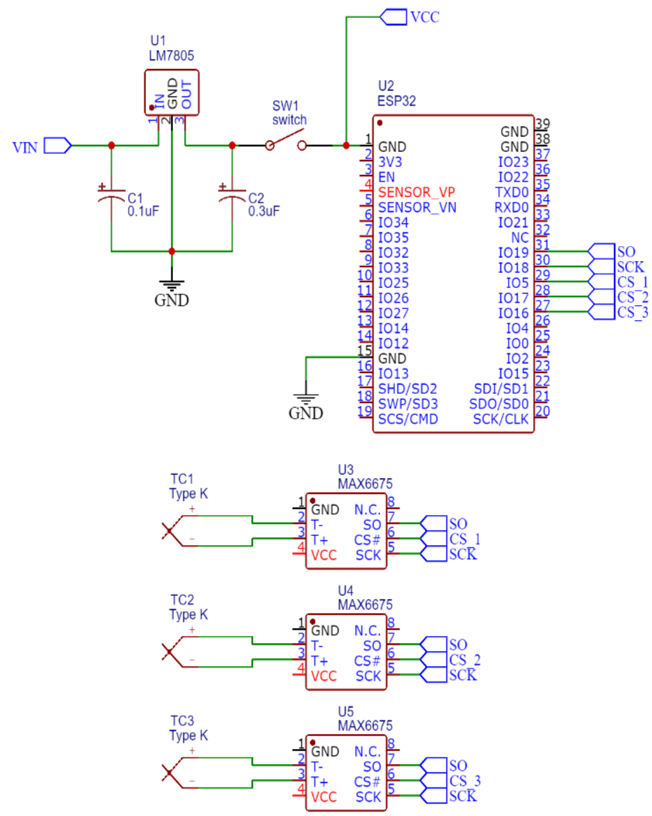

Fig. 3 Temperature sensor electronic circuit

4.1.2. Microcontroller and Data Processing

For this system, the ESP32 model was chosen to send information to the Python language due to its great versatility; for example, it supports communication protocols (SPI, I2C, and UART), and, above all, it has an integrated Wi-Fi and Bluetooth module. Using a pre-trained Random Forest model from Scikit-Learn, the control system developed in MicroPython can collect sensor data, preprocess it, and generate real-time temperature regulation predictions for the proposed system. The ESP32 encodes the temperature values and sends them to a local server once per second to ensure the accuracy of data collection. All readings obtained are stored for later analysis. The system also used a FIFO (First In, First

Out) buffer to prevent data loss and ensure no information is lost in the event of system interruptions due to a connection failure with the ESP32.

4.1.3. Voltage Regulator and Heaters Control

The system used a TRIAC-based control module to allow voltage modification of these types of components, the extruders, thereby achieving better control of the temperature-managing elements, making the system more optimal and efficient. An optocoupled trigger circuit (MOC3021) regulates the TRIAC (BTA16-600B), ensuring isolation between the microcontroller and the power grid, thus preventing damage to the system's most important components. By modulating the optocoupler's trigger signal using phase angle control methods, the ESP32 modifies the heater voltage based on the predictions of the pre-trained ML model. Compared to traditional on/off control, this method avoids sudden thermal fluctuations and allows for more precise modulation of the temperature output. By minimizing unnecessary on/off cycling and optimizing the power supply based on the observed temperature and the trend predicted by the ML model, this control system reduces power consumption, a significant contribution to the industry. Connection of the TRIAC module to the ESP32 and heaters: GND of the ESP32 to GND of the TRIAC module, GPIO23 of the ESP32 to the MOC3021 optocoupler trigger input, TRIAC output to the heating resistors (powered by 230V AC). In Figure 4, you can see all the connections that were previously explained.

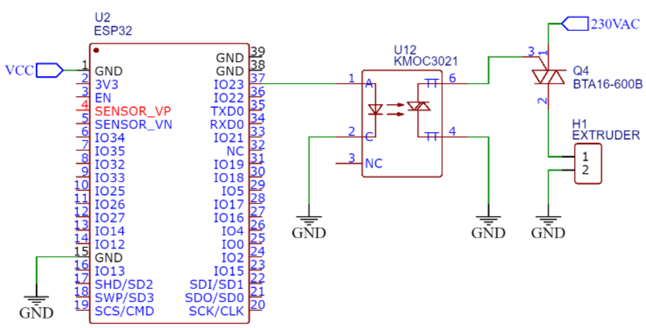

Fig. 4 Voltage regulators and heaters control the electronic circuit

4.1.4. Data Monitoring and Visualization Platform

The system incorporates a user interface designed to facilitate monitoring of the temperature management process based on the Flask and Plotly Python libraries. This interface allows users to view the temperature change in each extruder zone in real-time. This platform displays the temperature, applied voltage, and machine learning model predictions after receiving data from the ESP32 via a Wi-Fi connection. Additionally, this platform enables the creation of reports on thermal stability and energy efficiency as well as the export of data in CSV and JSON forms for offline study.

Figure 5 shows the connection of this system's key components, including the ESP32 microcontroller, temperature sensors (K-type thermocouples), the TRIAC module for voltage regulation, and the heating elements.

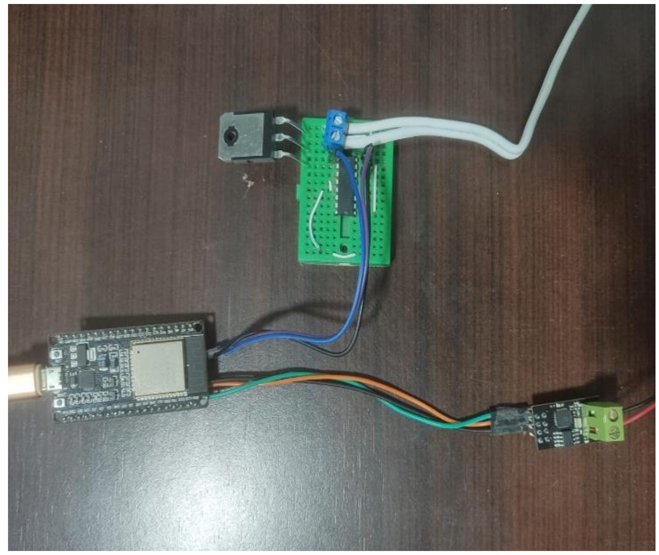

Fig. 5 Connection of electronic components

4.2. Preprocessing and Training of the Machine Learning Model

The preprocessing and training process of the Machine Learning (ML) model is fundamental to guarantee the accuracy and stability of the temperature control system in the extruder machine. This phase includes data collection and cleaning, normalization of variables, selection of relevant features, division of data into training and test sets, choice of the most suitable ML algorithm and optimization of hyperparameters to improve model performance.

4.2.1. Data Collection and Preprocessing

Data was obtained from K-type temperature sensors, which measure the temperature in three key areas of the extruder: the feed zone, the compression zone, and the dosing zone of the extruder analyzed in this system. These data were transmitted to the ESP32 microcontroller, which sent them to a local server via Wi-Fi. The data was stored in an SQLite database for later analysis, which would be carried out in subsequent work. The initial dataset contained records with temperature values (T) obtained every second (T = 1s), along with information about the applied voltage (V), operating time (t), and the feed rate of the material (S) reaching the extruder. However, due to communication failures, the raw data presented problems such as measurement noise, outliers, and incomplete records. After data cleaning, a refined dataset with over 100,000 temperature, voltage, and feed rate records was obtained, ready for analysis and modeling.

4.2.2. Normalization and Feature Selection

Since the magnitudes of the recorded variables vary significantly, min-max normalization was applied to scale the values within a range between 0 and 1, improving the stability of the model training. The normalization was performed using Equation (2):

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (2)$$

Where X represents the initial value, X_{min} and X_{max} represent the lowest and highest values of the variable in the dataset, respectively. This Random Forest approach was used to perform feature significance analysis to reduce information redundancy and improve the performance of the trained model. This research found the most important factors in predicting the system temperature. Capturing the thermal trend of the system requires the use of the previous temperature (T_{t-1}), which is the temperature data from the previous instant. The temperature changes were directly affected by the applied voltage (V), which represents the amount of power supplied to the heating element at a given time. Finally, the feed rate (S), which reflects the relationship between the volume of extruded material and the internal temperature, also played a significant role in the model's predictive accuracy. For this research, variables considered less important, such as time of day or small fluctuations in ambient temperature, were discarded to reduce the complexity of the model without affecting its accuracy.

4.2.3. Machine Learning Model Training

First, the dataset was split into two subsets, one for training and the other for evaluating model performance. The model was trained using 70% of the data (X_{train}, Y_{train}) so that it could learn and modify its internal parameters. The remaining 30% (X_{test}, Y_{test}) was reserved for testing, allowing for an objective assessment of the model's ability to generalize to new and untested data.

This split was done in a stratified manner, ensuring that both parts had a similar distribution of temperatures, voltages, and feed rates. Several supervised learning algorithms were compared to determine which offered the best accuracy and generalization capabilities for temperature prediction. The following models were evaluated: Multiple Linear Regression, which offered acceptable performance under static conditions but showed difficulties adapting to dynamic temperature variations; Artificial Neural Network (ANN), which showed good accuracy but with longer training times and lower interpretability; Random Forest Regressor, it showed the best balance between accuracy, response time, and robustness to system variations. The Random Forest model was chosen for final implementation in the control system because it provided the lowest Mean Square Error (MSE = 0.27) and was flexible enough to handle historical data without overfitting.

To train the Random Forest model, 100 decision trees and a variance reduction (MSE)-based partitioning criterion were used. When tested on the test set, the trained model's coefficient of determination (R^2) was 0.94, demonstrating high accuracy in temperature prediction, which was key to its selection. Due to the limited processing power of the ESP32, numerous methods were developed to optimize the Random Forest model for real-time execution. First, it was converted to TensorFlow Lite (TFLite), a lightweight format suitable for microcontrollers.

The use of Edge AI inference then allowed the model to run locally on the ESP32 without relying on external servers, ensuring faster and more reliable performance. The C++ code was additionally enhanced using the uTensor package in the Arduino IDE, which decreased memory use without compromising accuracy. The enhanced model's 3ms inference time resulted in a significant improvement in the system's responsiveness and efficiency.

4.3. Implementation of the Control System

The crucial stage in creating the experimental system was installing the machine learning-based temperature control system for the extrusion machine. In this step, the extruder hardware was successfully integrated with the trained ML model, and a control system was designed to be capable of dynamic temperature adjustments based on predictions obtained from the model previously trained by the research team. The objective was to automatically adjust the voltage applied to the heaters based on the thermal conditions of the system in order to maintain the temperature within the ideal range for the extrusion process. The following is a description of how each component of the control system was implemented and their interaction.

4.3.1. Real-Time Control System Design

The closed-loop design of the control system ensures continuous temperature regulation, with only small adjustments in response to temperature sensor data. The ML model acts as the system controller by predicting the voltage needed to maintain the temperature within the designated range. The system input is the temperature reading from the K-type thermocouples, and its output is the voltage applied to the extruder heaters. Because it can monitor the execution of the machine learning models in real-time while collecting data from the sensors, the ESP32 microcontroller was chosen as the central processing unit. This microcontroller, despite being small, is capable of receiving temperature measurements every second via an SPI connection to the temperature sensors. Additionally, the ESP32's built-in Wi-Fi module allows for real-time data sharing for remote viewing.

4.3.2. Voltage Regulation through the TRIAC Module

Controlling the amount of heat produced by the extruder's heating elements allows for system temperature management. A TRIAC was used to regulate the Alternating Current (AC) supplying the extruder to achieve optimal voltage control by phase angle instead of using traditional on/off control, which is known to cause thermal fluctuations. The TRIAC module used is a switch controlled by a microcontroller, which allows the amount of power delivered to the heaters to be regulated by modulating the phase of the AC signal. An optocoupler (MOC3021) isolates the microcontroller from the 230V AC mains supply electrically. This control device allows for smooth, progressive voltage regulation, which helps prevent temperature fluctuations and contributes to thermal stability. The TRIAC trigger signal is generated by the ESP32, which adjusts the signal phase based on the ML model's predictions.

4.3.3. Dynamic Voltage Adjustment Based on the ML Model

The essential component of the control system is the pre-trained Random Forest model, which predicts the voltage required to maintain the temperature between the ideal range of 230°C and 250°C. The challenge was to incorporate this model into the ESP32 microcontroller due to its limited memory capacity, which is why a complete translation into a more efficient and smaller format was necessary. Using the TensorFlow Lite tool, the model was optimized to run with low latency and without compromising accuracy. Every second, the ESP32 receives the temperature reading from the sensors and passes it as input to the ML model.

The model, which has been trained to identify patterns between temperature, voltage, and feed rate, generates a prediction of the voltage adjustments needed to maintain a stable temperature. This predicted voltage is used to calculate the appropriate phase angle to send to the TRIAC module. In essence, the ML model autonomously adjusts the voltage applied to the heater resistors to minimize thermal fluctuations.

4.3.4. Implementation of an Adaptive Control Algorithm

The control system is characterized by its adaptability, as it can adjust in real-time to variations in operating conditions. This is achieved through an adaptive control algorithm that adjusts both the prediction model and the output voltage as the system experiences new conditions. In an industrial environment where material characteristics (such as viscosity) and because external fluctuations can be detrimental, the system's flexibility is crucial to avoid these problems. The system features a module for periodic recalibration of the machine learning model to ensure this flexibility. Furthermore, the system was designed to use the most recent data and update the prediction model at predetermined intervals to maintain its accuracy and flexibility. When the initial conditions under which the system was trained change, for example, the feed rate or the type of extruded material, this recalibration is crucial to avoid errors in the calculations of the developed algorithm.

4.3.5. Remote Monitoring and Control Interface

A monitoring interface was created during the installation to facilitate system performance management and temperature data visualization. An interactive dashboard was created using Flask as the web server platform and PlotlyDash for real-time data visualization. To provide constant monitoring and control, this dashboard allows operators to monitor temperature readings, voltage changes, and the overall status of the extrusion process of the developed system.

Furthermore, the user interface allows the system to respond to different manufacturing conditions and materials, allowing for modification of operating parameters such as the target temperature range or the model recalibration rate. The system also added the ability to store all sensor data in a local database, enabling comprehensive energy efficiency and thermal performance reports for process improvement.

5. Results and Discuss

The outcomes of the single-screw extruder's Machine Learning (ML)-based heat control system are shown in this section. Thermal stability, stabilization time, and energy efficiency are taken into consideration when comparing the performance metrics of the suggested model to those of a conventional PID controller. Tables showing the improvements made with the ML-based system are presented, along with the values obtained and the explanation that goes with them.

5.1. Thermal Stability and Control Accuracy

One of the main objectives of this system is to reduce temperature variations during the extrusion process. For 60 minutes, the research team monitored the temperature in three different areas of the extruder barrel to evaluate its thermal stability and controllability. The difference between the current temperature and the set temperature (240 °C) was recorded every second. The root mean square error and standard deviation were calculated for each control method. Table 1 presents a comparison between PID control and machine learning control for extruder thermal stability.

Table 1. Comparison of thermal stability between PID and ML

Metrics	PID Control	ML Control	Improvement (%)
Standard deviation [°C]	3.52	1.86	47.2%
Mean square error [°C²]	12.41	3.65	70.6%
Maximum fluctuation (°C)	± 5.8	± 2.3	60.3%

These results demonstrate that the developed ML-based system exhibits less fluctuation compared to the traditional PID method. The 47.2% reduction in standard deviation showed a smaller dispersion of the temperature data around the set point. Furthermore, the root Mean Square Error (MSE) was reduced by 70.6%, indicating greater precision in thermal regulation. Furthermore, the largest temperature variation with PID control was ±5.8°C, but the ML system reduced it to ±2.3°C, demonstrating improved process stability and ensuring improved product quality.

5.2. Stabilization Time

Stabilization time is a key metric for evaluating how quickly the control system manages to reach the stable temperature range (±2°C from the 240°C setpoint) after an initial disturbance or startup. Tests were performed in which the extruder was started from room temperature to operating temperature, and the time required for the temperature to remain within the stability range was measured. A comparison of the time required to achieve stabilization between PID control and machine learning control is shown in Table 2.

Table 2. Comparison of stabilization time

Condition	PID Control	ML Control	Improvement (%)
From room temperature (25°C) [min]	12.4	9.1	26.6%
Recovery after perturbation (±10°C) [s]	48.2	32.7	32.2%

Compared to PID control, the ML control system enabled a 26.6% reduction in initial stabilization time, allowing the extruder to begin production sooner, reflecting significant optimization for the production line. This is because the ML model avoids sudden changes and reduces lead time by dynamically predicting the ideal voltage based on temperature conditions. Furthermore, when artificial temperature disturbances (due to changes in material feed rate) were introduced, the recovery time with ML control was 32.7 seconds, compared to 48.2 seconds with PID, improving the system's ability to react to changes in operating conditions. Figure 6 shows the two curves generated from the temperature values in °C of the model with PID and with ML.

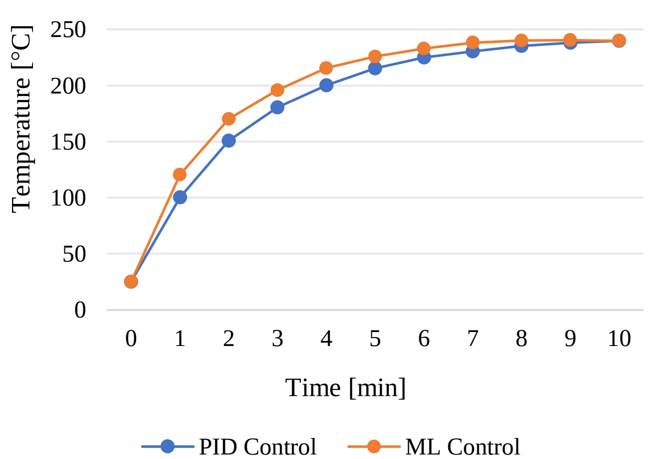

Fig. 6 Stabilization time graph

Figure 6 shows a slower stabilization by the PID control, reaching the reference temperature in 10 minutes with small fluctuations thereafter. On the other hand, the machine learning control achieves faster stabilization in 8 minutes, with minimal variation from minute 7 onward.

5.3. Energy Consumption and Efficiency

The energy usage of the heating system was another crucial aspect evaluated during installation, as better control should save unnecessary energy use. The extruder's total power consumption was measured throughout the course of four hours of continuous operation, comparing the energy consumption of the two control techniques. A comparison of PID control and machine learning control's energy usage is displayed in Table 3.

Table 3. Comparison of energy consumption

Metrics	PID Control	ML Control	Savings (%)
Total consumption in 4h [kWh]	5.82	4.76	18.2%
Energy wasted due to overheating [kWh]	0.94	0.23	75.5%

Compared to a conventional PID, the ML system reduced total energy consumption by 18.2%, resulting in lower operating costs and more efficient use of thermal energy. Furthermore, the research revealed that the ML-based system improved thermal management by 75.5%, reducing the energy loss caused by PID control from 0.94 kWh due to overheating and sudden adjustments to 0.23 kWh. In addition to cost savings, these energy savings also reduce the carbon footprint of the industrial process, which supports more environmentally friendly production techniques.

6. Conclusion

This work demonstrated a Machine Learning (ML)-based thermal control system for extrusion machines that predicts and dynamically modifies the voltage supplied to the heating resistors using a random forest model. A closed-loop control system was implemented, in which the ESP32 microcontroller used a TRIAC module to modify the voltage after receiving real-time data from temperature sensors and executing the pre-trained ML model with data obtained from the temperature sensors. Experimental results showed that ML control significantly outperformed traditional PID control across all evaluated metrics, thus validating the proposed system's suitability for application.

First, it improved thermal stability, with a 47.2% reduction in temperature standard deviation and a 70.6% reduction in Mean Square Error (MSE), resulting in more precise and consistent thermal control over time. Stabilization time was also reduced, resulting in greater adaptability of the ML system, demonstrated by a 26.6% reduction in the time required to reach the target temperature from ambient temperature and a 32.2% reduction in recovery time from thermal disturbances that could occur in a typical industrial environment. Finally, energy consumption was optimized, as evidenced by the significant reduction in operating costs and improved process efficiency achieved by the Machine Learning (ML)-based system, which reduced energy expenditure by 18.2% and energy waste due to overheating by 75.5%. These results demonstrate that, compared to conventional PID-based methods, incorporating ML techniques into thermal control systems offers several advantages, such as the sustainability of the industrial process, reduced energy costs, and improved final product quality. In the future, plans are underway to develop an IoT-based infrastructure where data collected by the system can be sent to a cloud platform for real-time analysis, historical data storage, and remote monitoring. This would allow for implementing a Big Data-based predictive and autonomous control system. Although the Random Forest model showed solid performance, more advanced models such as Recurrent Neural Networks (RNN) or Long Short-Term Memory (LSTM) may be able to further improve the prediction capability, especially in extrusion processes with higher variability.

Acknowledgments

The authors of this article would like to thank the Universidad Nacional de San Agustín de Arequipa for its continued support and resources provided during the development of this research.

References

[1] Marko Hyvärinen, Rowshni Jabeen, and Timo Kärki, "The Modelling of Extrusion Processes for Polymers-A Review," *Polymers*, vol. 12, no. 6, pp. 1-14, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] Adrian Lewandowski, and Krzysztof Wilczyński, "Modeling of Twin Screw Extrusion of Polymeric Materials," *Polymers*, vol. 14, no. 2, pp. 1-28, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[3] Christian Marschik, Wolfgang Roland, and Tim A. Osswald, "Melt Conveying in Single-Screw Extruders: Modeling and Simulation," *Polymers*, vol. 14, no. 5, pp. 1-32, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] Takao Sato et al., "Performance-Adaptive Generalized Predictive Control-Based Proportional-Integral-Derivative Control System and Its Application," *Journal of Dynamic Systems, Measurement, and Control*, vol. 136, no. 6, pp. 61-67, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[5] Chamil Abeykoon, Alison McMillan, and Bao Kha Nguyen, "Energy Efficiency in Extrusion-Related Polymer Processing: A Review of State of the Art and Potential Efficiency Improvements," *Renewable and Sustainable Energy Reviews*, vol. 147, pp. 1-24, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[6] André Silva et al., "A New Approach to Temperature Control in the Extrusion Process of Composite Tire Products," *Journal of Manufacturing Processes*, vol. 65, pp. 80-96, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[7] Stephan Handschuh-Wang, Florian J. Stadler, and Xuechang Zhou, "Critical Review on the Physical Properties of Gallium-Based Liquid Metals and Selected Pathways for Their Alteration," *The Journal of Physical Chemistry C*, vol. 125, no. 37, pp. 20113-20142, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Chamil Abeykoon, "Single Screw Extrusion Control: A Comprehensive Review and Directions for Improvements," *Control Engineering Practice*, vol. 51, pp. 69-80, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[9] Adam E. Jakus et al., "Metallic Architectures from 3D-Printed Powder-Based Liquid Inks," *Advanced Functional Materials*, vol. 25, no. 45, pp. 6985-6995, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[10] A.N.M. Amanullah et al., "Design and Development of a Hybrid Machine Combining Rapid Prototyping and CNC Milling Operation," *Procedia Engineering*, vol. 184, pp. 163-170, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[11] Leonardo Daniel Cuadros Palomino et al., "Design and Construction of a Real Time Monitoring System with Raspberry Pi and WhatsApp Applied in a Water Tank for Agriculture," *International Journal of Electrical and Electronics Engineering*, vol. 11, no. 4, pp. 217-225, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] Sergiu Pascu, Adrian Augustin Pop, and Nicolae Balc, "Design and Development of SP Hybrid Manufacturing Prototype Combining 3D printing and CNC Milling," *2023 10th International Conference on Modern Power Systems*, Cluj-Napoca, Romania, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Alexander A. Oskolkov, Igor I. Bezukladnikov, and Dmitriy N. Trushnikov, "Rapid Temperature Control in Melt Extrusion Additive Manufacturing Using Induction Heated Lightweight Nozzle," *Applied Sciences*, vol. 12, no. 16, pp. 1-21, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] David A. Anderegg et al., "In-Situ Monitoring of Polymer Flow Temperature and Pressure in Extrusion Based Additive Manufacturing," *Additive Manufacturing*, vol. 26, pp. 76-83, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[15] Luquan Ren et al., "Process Parameter Optimization of Extrusion-Based 3D Metal Printing Utilizing PW-LDPE-SA Binder System," *Materials*, vol. 10, no. 3, pp. 1-16, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[16] Jialuo Han et al., "Exploring Electrochemical Extrusion of Wires from Liquid Metals," *ACS Applied Materials & Interfaces*, vol. 12, no. 27, pp. 31010-31020, 2020. [CrossRef] [Google Scholar] [Publisher Link]