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ICSINTESA

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Balikpapan - Indonesia

July 12, 2024

GLOBAL TECHNOPRENEUR CAMPUS

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Preface

The world is experiencing rapid technological advances and dynamic social changes; technopreneurs operating in the digital era must balance it with innovation and transformation. Technopreneurship combines elements of technology and entrepreneurship, facing new challenges and opportunities that require creative thinking and rapid adaptation. In the context of today's global world, technopreneurship refers to the activity of creating and managing a business based on technological innovation, with a particular focus on the use of the latest tools and methods, including artificial intelligence (AI) to the Internet of Things (IoT), technology provides tools for technopreneurs to create innovative and relevant solutions. AI includes a variety of technologies that enable machines to learn, analyze data, and make decisions automatically. Adopting agile methodologies allows technopreneurs to experiment quickly and respond to customer feedback. It not only increases competitiveness but also facilitates sustainable innovation. Technopreneurs play a crucial role in addressing environmental and social issues and must integrate sustainable practices into their business models. It includes developing environmentally friendly products, reducing waste, and implementing ethical production methods. AI enables technopreneurs to build more innovative and more responsive products and services. Businesses focusing on sustainability meet consumer expectations and strengthen their position as market leaders. By leveraging AI, technopreneurs can reduce operational costs and increase productivity. Previously time-consuming and resource-intensive processes can now be done faster and more accurately. Data is now considered a valuable asset in the business world. With greater access to big data, technopreneurs can use data analytics to identify trends, optimize operations, and understand customer preferences. This data-driven approach increases efficiency and enables more informed and strategic decision-making.

The International Conference of Science and Information Technology in Smart Administration (ICSINTESA) is an annual scientific meeting agenda that creates a space for experts to exchange knowledge and ideas. In this forum, participants can discuss the latest research, technology trends, and challenges faced in the industry. Scientific meetings provide a platform for professionals to stay updated with the latest information on research and technological developments, which is crucial for staying relevant in their fields. These meetings often catalyze innovation by discussing new ideas and the latest technologies, and active involvement in them is essential for individuals and organizations who want to stay at the forefront of technology. By participating in scientific meetings, professionals can gain insights, network with peers, and contribute to advancing their fields. Hopefully, this conference will significantly drive progress and innovation in various fields.

Editor in Chief
Ferry Wahyu Wibowo

Welcome

Welcome Statement
Chair of Conference

Assalamu'alaikum Warahmatullahi Wabarakatuh

Greetings to all,
Distinguished presenters and conference participants, esteemed guests, dedicated reviewers, and cherished attendees. I am immensely proud and grateful to welcome you all to this esteemed event. This year's conference has seen a significant increase in the number of paper submissions, with a total of 444 papers received from over 30 countries. Out of these, 137 papers have been meticulously selected through a rigorous review process conducted by our dedicated reviewers. Each paper was reviewed by three experts, reflecting our commitment to maintaining high scientific quality and integrity.
ICSINTESA 2024 marks the fourth iteration of this international conference, and we are proud to announce that the selected papers will be published in IEEE Xplore. The increased quality and quantity of accepted papers this year demonstrate the enthusiasm and trust of the academic community in this conference.
We aspire for Universitas Mulia to consistently uphold and enhance the quality of this seminar, establishing it as a benchmark for scientific conferences both in Indonesia and globally. I would like to extend my heartfelt thanks to all the organizers, reviewers, and participants who have contributed to this event. May we all gain valuable insights and inspiration from this conference, driving forward the advancement of knowledge and technology. With that, I wish you all an enriching and successful conference.
Wassalamu'alaikum Warahmatullahi Wabarakatuh

Warm Regard

Richki Hardi
Chair of Universitas Mulia Conference

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V   A B C D E F G H I K L M N O P R S T U V W

W   A B C D E F G H I K L M N O P R S T U V W

LabVIEW Integrated with Python Machine Learning for DC Motor Drive

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***Abstract*— This study presents a new technique that integrates LabVIEW and Python to enhance the control of DC motor drives through the utilization of machine learning methods. The objective of our research is to leverage LabVIEW's graphical programming interface in combination with the Scikit-learn Python package to train a Polynomial Regression model. The goal is to forecast Pulse Width Modulation (PWM) values at desired Rotations per Minute (RPM) of a DC motor. The accuracy and reliability of the trained model are evaluated using performance assessment metrics such as the R-squared (R^2) coefficient of determination and the Root Mean Square Error (RMSE). The R^2 score assesses the precision of the model's fit, whereas the RMSE quantifies the model's predictive capability by comparing observed and predicted data. This research also includes a comparison between the machine learning technique for DC motor drive and conventional PID control. The findings illustrate the successful integration of LabVIEW and Python in managing DC motor drives, achieving low overshooting and faster attainment of the set RPM point compared to classical PID control. This emphasizes machine learning's capacity to enhance control strategies; the application of Polynomial Regression yields promising results, demonstrating its effectiveness in predicting PWM and RPM values with an R^2 value ranging from 96% to 98% and RMSE within 19.**

Keywords—Labview, Python, Scikit-learn, Polynomial Linear Regression, DC motor Drive, EasyEda, Machine Learning, RMSE, R^2, PID

I. Introduction

The incorporation of various technologies has played a crucial role in enhancing the capabilities of engineering systems in recent years. The combination of hardware and software, along with the utilization of machine learning techniques, has created opportunities to improve the effectiveness and capability of different applications. Our project aims to integrate LabVIEW [1] and Python [2] to effectively drive and control DC motors using an intelligent machine learning framework. DC motors are essential components in a wide range of industrial applications, including robotics and automation systems [3]. Our work intends to leverage the benefits of LabVIEW, a versatile graphical programming environment, and Python, a sophisticated language extensively used in data science and machine learning [4], to create a control system based on a machine learning approach. The control system employs machine learning techniques to fine-tune and verify its performance using statistical tools such as R^2 for machine learning optimization, and RMSE for comparing predictions with actual outcomes. Additionally, the performance of the machine learning approach is compared with the conventional PID approach.

II. Literature Review

A. Machine Learning Techniques

Machine learning has progressed as a groundbreaking field, offering powerful tools to depict complex relationships inside data. It's a branch of artificial intelligence (AI), allows systems to autonomously learn and refine their performance based on experience, eliminating the need for human intervention. This technology enhances the predictive capabilities of software applications without the necessity for explicit programming. Fundamentally, machine learning focuses on creating algorithms that analyze input data and make predictions using statistical methods. In recent years, machine learning has become highly popular, with its algorithms being utilized in diverse areas such as object detection, pattern recognition, text interpretation, and various research disciplines. The main aim of machine learning is to teach computers to leverage data to address specific problems efficient [5]

In recent years, Machine Learning (ML) algorithms have been increasingly implemented, though some solutions may simply replace one problem with another. Common types of machine learning include supervised learning, unsupervised learning, and reinforcement learning [6].

Supervised learning involves using a dataset comprised of pre-labeled target data input variables (training data) [7]. This method generates a mapping function to associate inputs with the desired outputs based on these input variables. The model parameters are adjusted until it reaches a satisfactory level of accuracy with the training data. This type of learning allows for predictions based on a known dataset (training dataset), which includes input variables (X) and output/response variables (Y). These variables are essential for developing a model that predicts the value of the response variable (Y) for new, unseen data. In supervised learning, an algorithm is designed to learn the mapping function from the input variables (X) to the output/response variable (Y). The mapping function can be expressed as:

$$Y = f(X) \tag{1}$$

Unsupervised learning utilizes only training data without associated outcome data, meaning the data is not pre-classified. This approach identifies existing patterns or clusters within datasets without the need for supervision. The model autonomously discovers information to produce output, primarily dealing with unlabeled data. One of the most common methods in unsupervised learning is cluster analysis, which is used to identify structures or patterns within a pool of unclassified data [8].

Reinforcement learning involves conditioning a machine to take actions based on specific decisions, resulting in rewards or feedback. The machine is programmed to draw from past experiences to identify the most beneficial actions. This method enables the machine to take appropriate actions in given situations to maximize rewards. Learning occurs through interaction with the environment by agents or learners, who receive rewards for correct actions and penalties for incorrect ones. The agent learns without human intervention by aiming to maximize rewards and minimize penalties. This system of rewards and punishments effectively trains the algorithms [9].

B. Algorithm of Machine Learning

Decision tree algorithms are primarily utilized for classification problems. They divide attributes into two or more classes based on their values. Each tree consists of nodes and branches, where each node represents an attribute of the group, and each branch corresponds to a specific value of that attribute [10].

Artificial neural networks model themselves after the configuration of biological neurons and operate using a supervised approach to machine learning. They consist of artificial neurons interconnected with weighted connections between units. These networks are recognized for their capability in parallel distributed computing [11].

Data Clustering Algorithms partition objects into different groups or clusters based on similarities among items within each subset. It is an unsupervised learning method commonly referred to as clustering or hierarchical and network partitioning techniques [12].

Regression algorithms make predictions by modeling the relationship between variables using an error measure, predicting continuously varying values. This statistical tool helps identify the relationship between dependent and independent variables and is used to model a target value that relies entirely on independent predictors. Regression analysis is employed to find correlations between two variables, though it cannot determine cause-and-effect relationships. Unlike classification algorithms, which categorize output variables, regression focuses on predicting continuous outcomes [13].

Polynomial regression [14] is a type of regression algorithm which has versatile technique that is particularly valuable for assessing the relationship between data, especially when implemented using the Scikit-learn framework. This approach is highly significant in numerous disciplines [15].

C. Polynomial Regression Fundamentals

Polynomial regression, an extension of linear regression, is adept at capturing intricate nonlinear relationships. The literature extensively covers its fundamental principles, showcasing its capability to model data with higher degrees of complexity [16]. The general form of the polynomial regression equation is expressed as a polynomial function of the independent variable, allowing researchers to flexibly adapt models to the shape of the data.

D. Scikit-learn a Robust Toolkit for Polynomial Regression

Scikit-learn, a widely used machine learning library in Python, provides a comprehensive set of tools for implementing polynomial regression models. Researchers have embraced Scikit-learn for its efficient implementation and integration capabilities, enabling the seamless deployment of polynomial regression in diverse applications [17].

E. Pulse Width Modulation (PWM) for DC Motor Drives

Pulse Width Modulation (PWM) is a vital technology extensively used in the realm of DC motor drives to control the velocity and orientation of direct current (DC) motors [18]. This technology is crucial for achieving accurate control over motor performance, enabling efficient and dynamic modifications in a wide range of applications, including robotics and industrial automation. Pulse Width Modulation (PWM) functions by swiftly alternating a signal between an active state and an inactive one at a consistent frequency. The duty cycle is defined as the ratio of the duration in which the signal is in the "on" state (high voltage) to the overall period of the signal. Pulse Width Modulation (PWM) is a technique that allows for precise control of the average power output to a DC motor by adjusting the duty cycle. Pulse Width Modulation (PWM) enables speed control by adjusting the proportion of time the signal is on compared to the total time of the signal [19]. As the duty cycle increases, the motor experiences a greater average voltage, leading to an increase in speed. On the other hand, a decreased duty cycle results in a decrease in the average voltage and a reduction in the motor speed. This system enables seamless and uninterrupted speed regulation in DC motor drives.

III. Research Methodology

A. Hardware Design

The web-based software EasyEDA [20] was employed to create a schematic and PCB, integrating components such as a controller (ESP8266), opto-coupler isolator, IGBT drive, power regulator, and various discrete elements. This board is designed to drive the DC motor and record RPM speed for machine learning data collection. The schematic of this board is illustrated in Fig. 1 (a), utilizing the ESP8266 controller embedded with C code firmware. It functions as the bridge channel interfacing through the USB port between the LabVIEW-Python-based PC software, the DC motor drive, and the encoder reader. The board utilizes the IGBT as the switching drive for the DC motor and an opto-coupler to isolate the microcontroller drive signal from the electromagnetic induction generated by the DC motor. Voltage regulators are employed to regulate the power supply from the DC motor to match with the supply of the ESP8266 microcontroller, opto-coupler, and other components. The functionality of this PCB includes an RPM reading feature through the encoder, facilitating the measurement of the DC motor speed for data collection in the machine learning training module. The PCB shown in Fig.1 (b) is generated from this schematic using the same EasyEDA software, with the 3D view shown in Fig. 1 (c). The assembled PCB, featuring components for a complete PCBA for the DC motor drive with data collection for machine learning, is depicted in Fig. 1 (d).

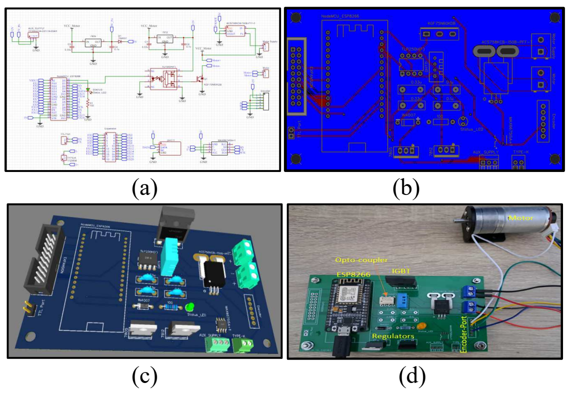


Fig. 1 (a) Schematic of DC Motor Drive, (b) PCB layout of DC Motor Drive , (c) PCB (3D) of DC Motor Drive, (d) PCBA of DC Motor Drive

B. Software System Design

LabVIEW is primarily used as the graphical user interface (GUI) for this system, sending PWM signals to the ESP8266 controller to control the IGBT, thereby turning the DC motor on and off. Additionally, LabVIEW is employed to read the RPM speed of the DC motor through the encoder. The interfacing between the DC motor drive board and the PC is achieved through the USB port. The dataset of PWM and RPM values is recorded in a text file for further processing in

Python's text-based coding software. This Python software is designed to invoke the Scikit-learn library's train module, establishing the relationship between PWM (%) and RPM, with the R-Squared value calculation for the model's predictive accuracy. Then, after the LabVIEW software is triggered by the user to predict the PWM (%) value needed to be sent to the DC motor drive board for achieving the desired RPM, LabVIEW will call the Python to predict value. This function predicts the PWM(%) value required for the specified RPM using the trained model previously executed. In addition, this LabVIEW-Python integrated software also includes a test mode to collect the data for evaluating the trained model using the Root-mean-square deviation (RMSE) value. This value represents the difference in error between the trained model and the real values generated from the predict function. The overview flow diagram of this software system is shown as the Fig. 2.

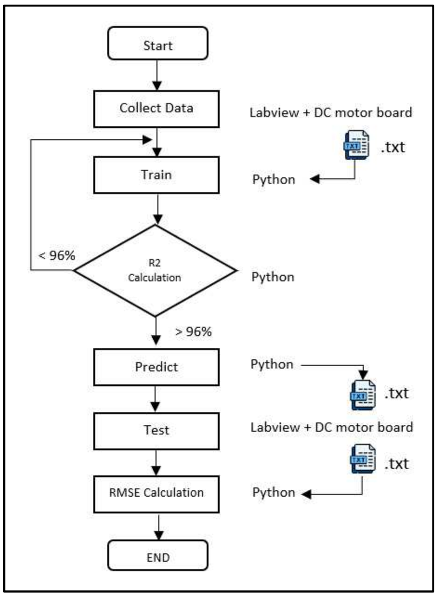
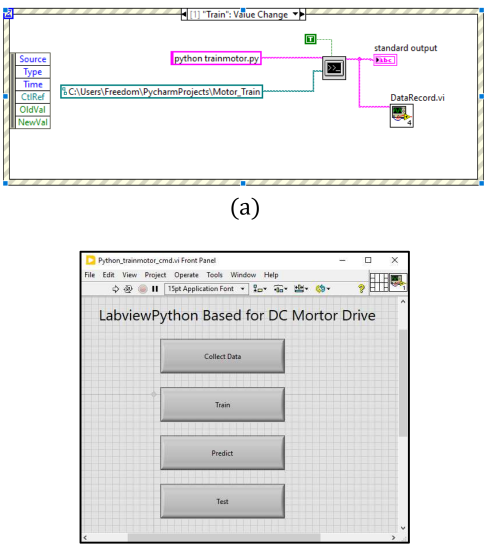


Fig. 2 Software Flow Diagram

The interface between LabVIEW and Python is established through the CMD tool as shown in Fig. 3 (a) and the user interface is shown as Fig. 3 (b), which calls the Python script and facilitates the interchange of data with a text-based file.



(b)

Fig. 3 (a) Labview Call Python Script
(b) Labview User Interface

C. Polynomial Regression

The train model is used the polynomial method to find the relation between the input and output as the equation below.

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \ldots + \beta_n X^n \quad (2)$$

Where Y is the predicted output, X is the input variable and $\beta_0, \beta_1, \ldots, \beta_n$ are the coefficients.

D. RMSE Calculation for Model Evaluation

The Root Mean Square Error (RMSE) is used to objectively evaluate the accuracy of machine learning models by comparing their predictions to the actual values. The equation for Root Mean Square Error (RMSE) is provided as follows.

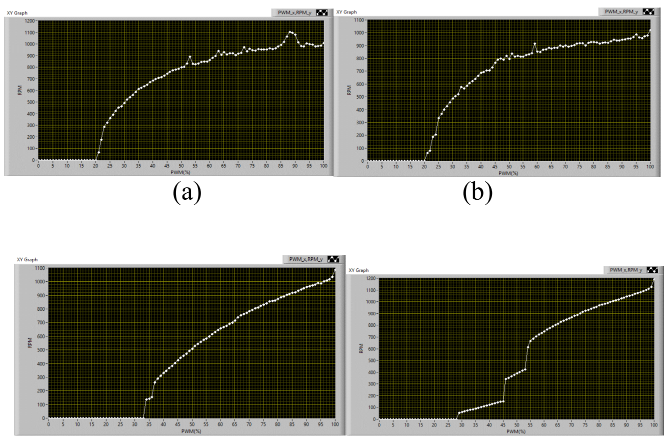
$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_{actual,i} - Y_{predict,i})^2} \quad (3)$$

Where N is the number of observation, $Y_{actual,i}$ is the actual value, $Y_{predict,i}$ is predict value.

IV. Results and Discussions

A. Machine Learning DC Motor Train and Drive

The LabVIEW-based software is executed to send the PWM value as a percentage to the ESP8266, which drives the IGBT in PWM mode to generate power for the DC motor. It also records the RPM value of the DC motor sent back from the encoder along with the PWM (%) value applied to the DC motor. The X-Y graph illustrating the relationship between the PWM (%) and RPM values, plotted by LabVIEW, is shown in Fig. 4. This graph demonstrates that the PWM (%) and RPM values exhibit unique characteristics under different conditions. For this experiment, two models of DC motors are used, 25GA371 (12VDC, 1000 rpm) and GA25370 (6VDC, 1360 rpm), under two conditions: no load and with load. The systems used are shown in Fig. 5.



(a) (b) (c) (d)

Fig. 4 The X-PWM(%), Y-RPM graph plotted by LabVIEW shows the relationship between the PWM(%) and the RPM values read back from the encoder : (a) 25GA371 DC Motor without load, (b) 25GA371 DC Motor with load, (c) GA25370 DC Motor without load, (d) GA25370 DC Motor with load

Fig. 5 (a) 25GA371 DC Motor without load, (b) 25GA371 DC Motor with load, (c) GA25370 DC Motor without load, (d) GA25370 DC Motor with load

Then, after recording the PWM (%) and RPM values of the DC motor, the Python code is used to train the model with a polynomial degree from 1 to 4 from the Scikit-learn library. The fitted model is plotted as shown in Fig. 6 to 9, along with the calculation of the R^2 value. Which, it seems that a polynomial of degree 4 fits well, as indicated by the high R^2 score [21] at around 96 to 98%. And, the summary of R^2 is shown in the Table I.

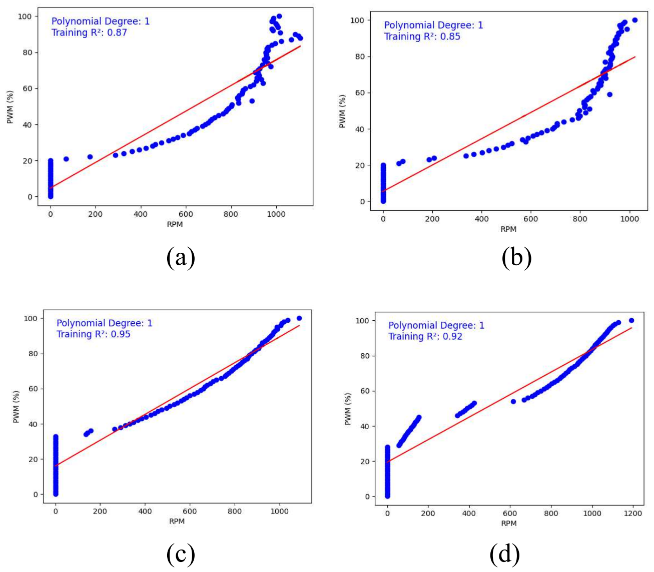


Fig.6 Polynomial plot degree 1 with trend line between RPM and PWM (%), (a) 25GA371 no load, (b) 25GA371 with load, (c) GA25-370 no load, (d) GA25-370 with load

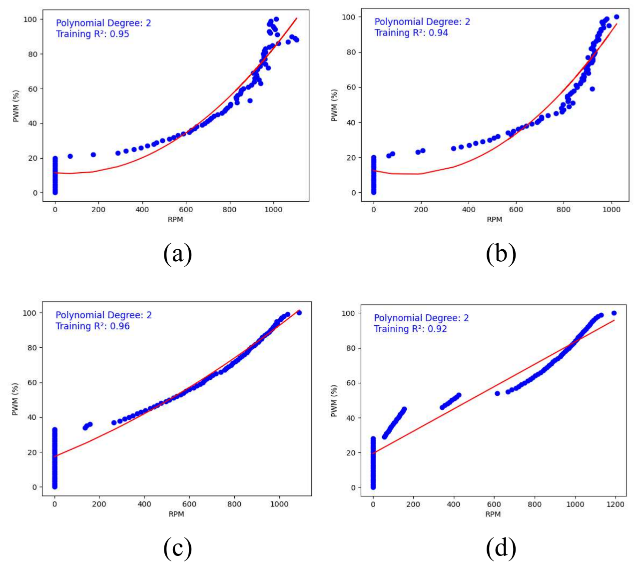


Fig.7 Polynomial plot degree 2 with trend line between RPM and PWM (%), (a) 25GA371 no load, (b) 25GA371 with load, (c) GA25-370 no load, (d) GA25-370 with load

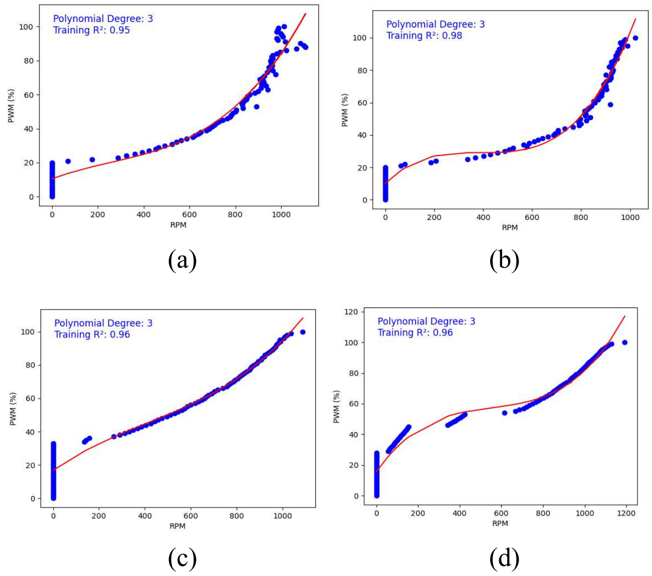


Fig.8 Polynomial plot degree 3 with trend line between RPM and PWM (%), (a) 25GA371 no load, (b) 25GA371 with load, (c) GA25-370 no load, (d) GA25-370 with load

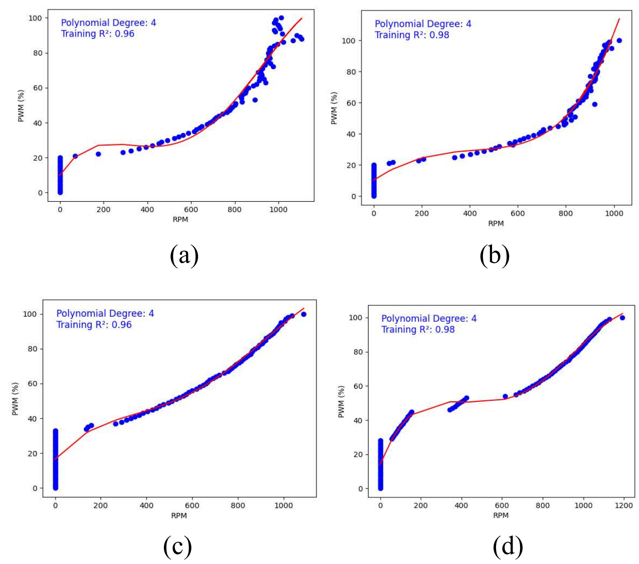


Fig.9 Polynomial plot degree 4 with trend line between RPM and PWM (%), (a) 25GA371 no load, (b) 25GA371 with load, (c) GA25-370 no load, (d) GA25-370 with load

TABLE I. R^2 SUMMARY OF POLYNOMIAL DEGREE 1 TO 4

System	Condition	Polynomial Degree			
		1	*2*	*3*	*4*
25GA371	No load	87%	95%	95%	96%
25GA371	No load	85%	94%	98%	98%
GA25-370	With load	95%	96%	96%	96%
GA25-370	With load	92%	92%	96%	98%

And, after completing the training, the test command from LabVIEW is executed to compare the predicted values with the actual values and observe the error, which is shown as Table II to Table V and the Root-mean-square error (RMSE) [22] value is calculated.

TABLE II. RMSE CALCULATION BETWEEN DESIRE RPM VS. ACTUAL RPM 25GA371 NO LOAD

Desire RPM	PWM (%) Predict	Actual RPM			Average	SD	Diff
		1	*2*	*3*			
400	36.85	430	435	441	435	5	35
500	40.78	489	492	494	492	3	-8
600	45.18	593	594	595	594	1	-6
700	50.38	683	683	686	684	2	-16
800	56.62	780	780	781	780	1	-20
900	64.09	893	894	896	894	1	-6
					RMSE		18

TABLE III. RMSE CALCULATION BETWEEN DESIRE RPM VS. ACTUAL RPM 25GA371 WITH LOAD

Desire RPM	PWM (%) Predict	Actual RPM			Average	SD	Diff
		1	*2*	*3*			
400	29.24	390	406	400	399	8	-1
500	30.54	501	513	495	503	9	3
600	33.21	600	611	600	604	6	4
700	39.30	710	719	705	711	7	11
800	51.28	801	798	795	798	3	-2
900	71.98	920	929	950	933	16	33
					RMSE		14

TABLE IV. RMSE CALCULATION BETWEEN DESIRE RPM VS. ACTUAL RPM GA25-370 NO LOAD

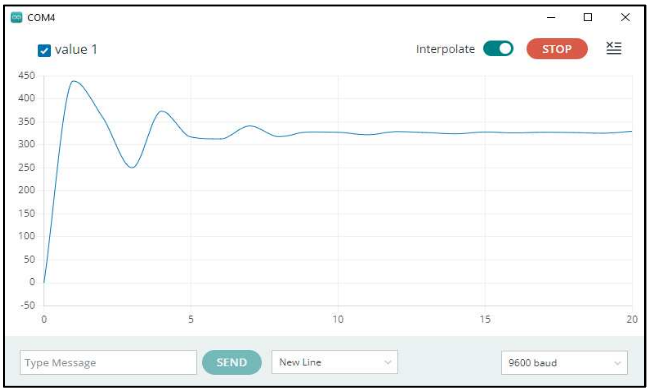
Desire RPM	PWM (%) Predict	Actual RPM			Average	SD	Diff
		1	*2*	*3*			
400	44.38	397	392	403	397	6	-3
500	48.92	501	491	509	501	9	1
600	54.90	601	600	598	600	2	0
700	62.72	717	707	707	710	6	10
800	72.32	795	793	797	795	2	-5
900	83.17	921	897	899	906	14	6
					RMSE		5

TABLE V. RMSE CALCULATION BETWEEN DESIRE RPM VS. ACTUAL RPM GA25-370 WITH LOAD

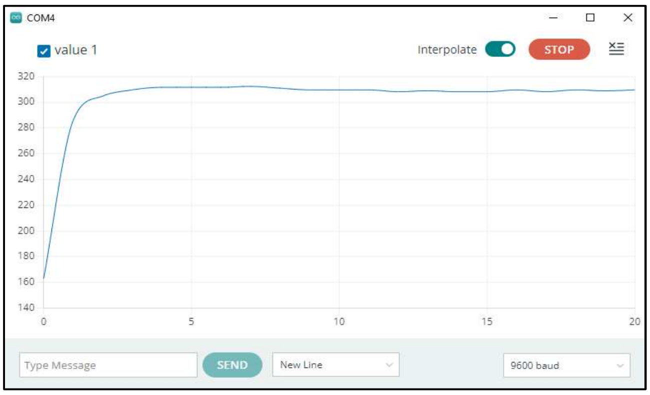
Desire RPM	PWM (%) Predict	Actual RPM			Average	SD	Diff
		1	*2*	*3*			
400	50.59	450	416	414	427	20	27
500	50.40	473	473	501	482	16	-18
600	51.78	560	610	599	590	26	-10
700	55.93	674	712	679	688	21	-12
800	63.24	769	802	767	779	20	-21
900	73.26	929	915	922	922	7	22
					RMSE		19

B. Machine Learning DC Motor Drive Comparing with Conventional PID Control

In the present study, the DC motor drive system, which incorporates the machine learning concepts discussed in the previous experiment from the earlier section, is meticulously compared with a traditional Proportional-Integral-Derivative (PID) control approach [24]. This comparison is conducted under identical conditions, specifically using the 25GA371 motor under no load. The performance evaluation involves capturing the revolutions per minute (RPM) of the motor over a specified time interval, immediately after the command is issued from the PC to achieve a particular RPM. The resulting data, as illustrated in Fig. 12, reveals that the motor drive employing the machine learning method exhibits a significantly lower overshoot in RPM compared to the conventional PID control. Furthermore, the machine learning-based drive achieves the desired RPM in a noticeably shorter duration. This underscores the enhanced efficiency and responsiveness of the machine learning approach over the conventional PID method in controlling the DC motor drive.



(a)



(b)

Fig. 12 Graph of RPM speed on y-axis and time (sec) on x-axis (a) Conventional PID control for DC motor drive (b) Machine Learning control for DC motor drive

V. CONCLUSION

This study successfully demonstrated the combination of LabVIEW and Python to enhance the capabilities of DC motor drive control. Using the Scikit-learn Python package, we employed polynomial regression as a machine learning technique [23] to predict the PWM (Pulse Width Modulation) percentage command required to achieve the desired speed (RPM) of a DC motor. This approach was compared with conventional PID control, which typically has higher overshoot and requires more time to reach the target RPM value. The conventional method also involves complex fine-tuning of P, I, and D values to reduce overshoot and quickly reach the RPM set point. The machine learning concept introduced in this paper addresses these issues. The smooth interface between LabVIEW and Python enabled rapid data transmission and model training, signifying a significant advancement in control system design. Polynomial regression yielded positive results in predicting the PWM % value. The accuracy of the model was evaluated by comparing the observed and predicted values, utilizing the Root Mean Square Error (RMSE). The attained RMSE is within 19 serves as a benchmark for assessing the predictive capabilities of our integrated system. This study establishes a solid foundation for the partnership between LabVIEW and Python in the realm of machine learning-driven control systems.

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