ANALYSIS OF THEORETICAL AND EXPERIMENTAL EFFICIENCY OF COMBINING KALMAN FILTER AND PID FOR DC MOTOR SPEED CONTROL

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GENERAL INFORMATION

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KEYWORD

Kalman Filter;
PID;
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ABSTRACT

The Proportional-Integral-Derivative (PID) controller is a widely used automatic control method in various fields. Numerous tuning methods have been developed to achieve optimal performance for PID control systems. This paper presents the design of a PID control system combined with a Kalman filter, capable of maintaining optimal performance for DC motors based on the Integral of Absolute Error (IAE) criterion. The IAE value for the classical PID is 1.1872, while the IAE value for the combined system (Kalman filter integrated with the PID controller) K_PID is 0.769. Experimental results demonstrate that integrating the Kalman filter significantly improves the performance of the PID controller, particularly in minimizing the impact of noise.

1. INTRODUCTION

DC motors are still used in research (Ravi Kiran Achanta, Vinay Kumar Pamula, 2017) and industrial applications (A. Ma’arif et al., 2020) because of their many advantages. They have good velocity regulation, provide high torque, quick response times, and high efficiency (M. A. Taut et al., 2018). These features ensure their used in various applications: conveyors, robots, and automation systems (Saad Chaouch, Mourad Hasni et al.,2018.).

To control DC motor, PID controllers are favored for their fast response, robustness to load variations, and ease of performance adjustment through tuning parameters Ki, Kp, and Kd. 90% of commercial and industrial applications are PID algorithm (A. Taut et al., 2018). Various methods have been developed for tuning these parameters (Irina Cojuhari et al., 2022). Among these, Ziegler-Nichols and iterative feedback tuning are widely adopted for their simplicity, though they can be sensitive to noise, affecting the tuning process and final parameter accuracy.

While PID controllers are effective in ideal conditions, their performance can degrade in the presence of measurement noise (D. Fodorean et al., 2016). Measurement noise arises from sources such as electromagnetic interference, electrical signal distortion, or errors in signal processing (A. Ma’arif et al., 2019). This type of noise can distort feedback signals, resulting in control inaccuracies and reduced system stability. To achieve this, the Kalman filter is considered for its ability to provide optimal state estimates in linear systems by combine a system model with considerations for measurement noise (Priya Shree Madhukar. L .B. Prasad 2020). Unlike traditional state observers, which rely solely on the system model, the Kalman filter combines model predictions with noisy measurements, delivering superior state estimation and enhanced noise handling. Its recursive computation also makes it suitable for real-time applications (Seta Yuliawan1 et al., 2021).

Speed control of a DC motor utilizing a Kalman filter combined with a PID controller, demonstrating its performance in comparison to a conventional PID controller through simulations (Seta Yuliawan et al., 2021).

This paper aims to simplify the control block of a Kalman filter combined with a PID controller, implement it on hardware, acquire real-time data, and evaluate the controller's performance with and without the Kalman filter.

2. METHODOLOGY

2.1 Hardware Implementation

Hardware Setup: The Arduino Mega2560 will perform motor control tasks through the L298 module. The DC Motor: Rated voltage 12 volts; no-load current: 0.3 A; maximum current under load: 1.8 A; no-load speed: 130 rpm (130 revolutions per minute); maximum speed under load: 100 rpm (100 revolutions per minute); rated torque: 0.9 Kg.cm; maximum torque: 4.4 Kg.cm.

Encoder: Collects pulse counts per second to calculate the actual motor speed. The encoder has two channels, A and B, to measure speed; pulse count per revolution = 1980 pulses/rev. This data will be noisy due to electromagnetic interference, electrical signal distortion. The velocity signal is transmitted in real-time from Arduino to the computer via RS232 port. The hardware is implemented as in figure 1.

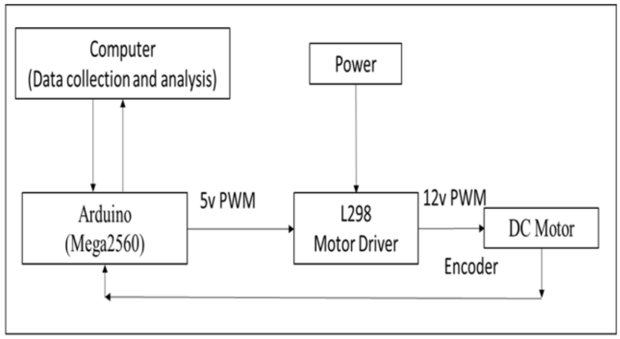

Figure 1. Hardware Block

2.2 Control designed

Kalman Filter, PID are programmed on Arduino to calculate and adjust the motor speed based on the error between the actual speed and the target speed.

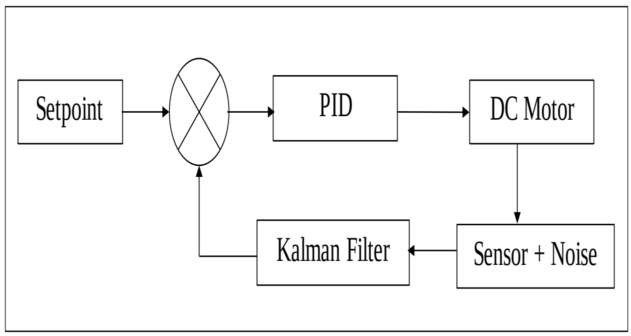

Figure 2. Control Block

The modeled for of discrete time of DC motor in equation (1). In order to have accurate control actions, the proposed controller needs to be brought into discrete time domain. PID control in the discrete time domain using forward discretization, as follows (M. A. Taut, et al., 2018):

$$u(t) = Kp \times e(t) + Ki \times \int e(t)dt + Kd \times \frac{de(t)}{dt} \quad (1)$$

In which: e(t) is the deviation between the desired speed value and the actual speed. u(t) is the control signal.

Kp, Ki, and Kd are the proportional, integral, and derivative gain coefficients, respectively. From here, the system will adjust the speed by changing the control signal u(t).

The Kalman Filter equation consists of two stages, the details of the used Kalman equation (G. Welch and G. Bishop 2001):

Prediction stage: This stage uses data from k-1 to calculate the state and confidence level of the system.

State estimation at time:....

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_k \quad (2)$$

Estimate the covariance matrix to measure the system's confidence level.

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q \quad (3)$$

In which: $\hat{x}_{k|k-1}$, is the predicted state, A is the system state matrix, and P is the covariance matrix.

Update stage: Update the predicted state and covariance matrix. This stage adjusts the estimate based on the measurement value and the predicted value.

- Update the Kalman Gain coefficient K_k:

$$K_k = P_{k|k\text{-}1}H^T(HP_{k|k\text{-}1}H^T + R)^{-1} \quad (4)$$

Update the state estimate at time K

$$\hat{x}_{k|k} = \hat{x}_{k|k\text{-}1} + K_k(z_k - H\hat{x}_{k|k\text{-}1}) \quad (5)$$

Update the covariance at time K

$$P_{k|k} = (I - K_k H)P_{k|k-1} \quad (6)$$

K_k, is the Kalman Gain matrix, Z_k is the measurement input from the encoder, H is the observation matrix, R is the measurement noise covariance matrix, và Q is the system noise covariance matrix.

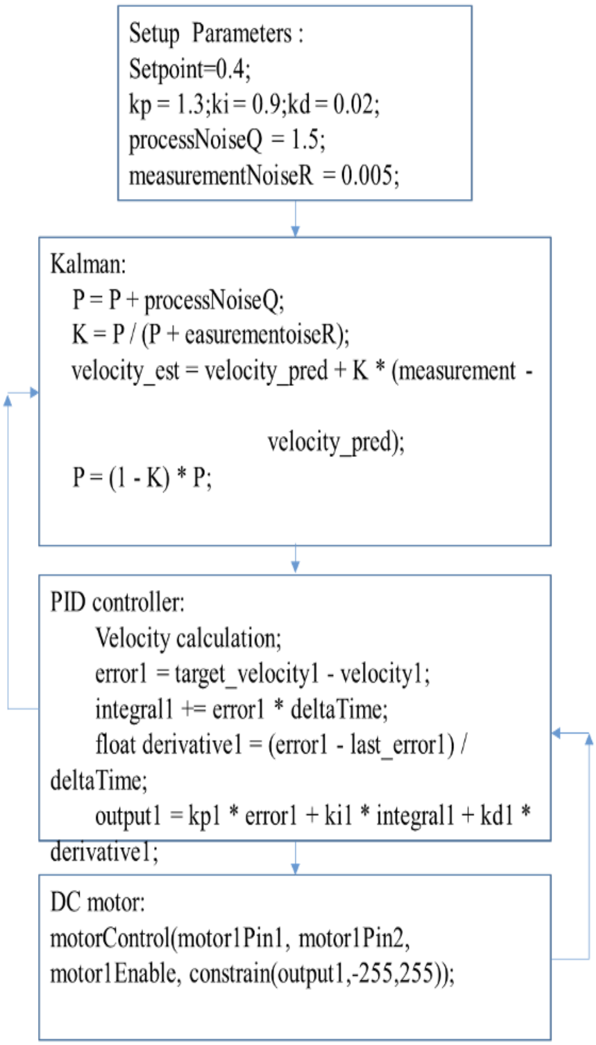

Figure 3. Algorithm flowchart

3. FINDINGS AND DISCUSSION

3.1 PID system without Kalman filter

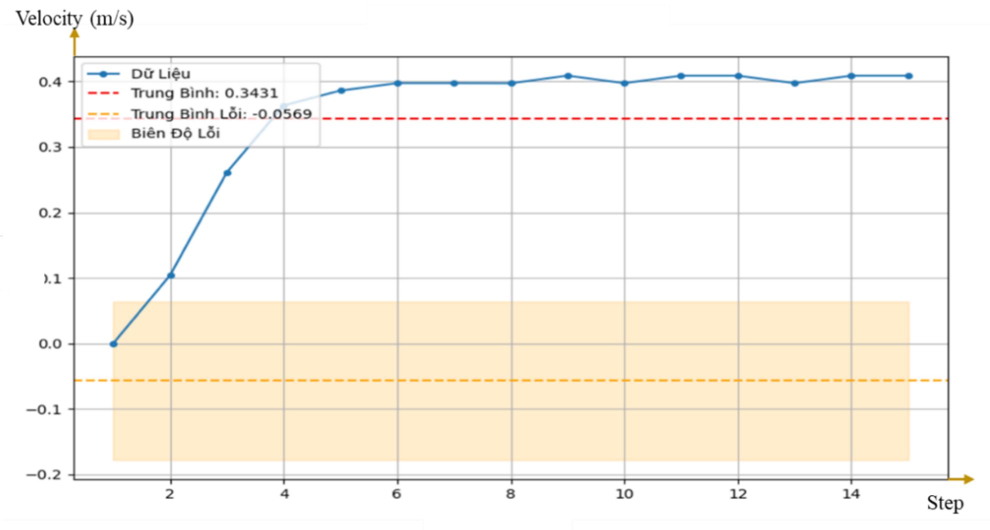

Figure 4 System Response with PID at 0-15 steps

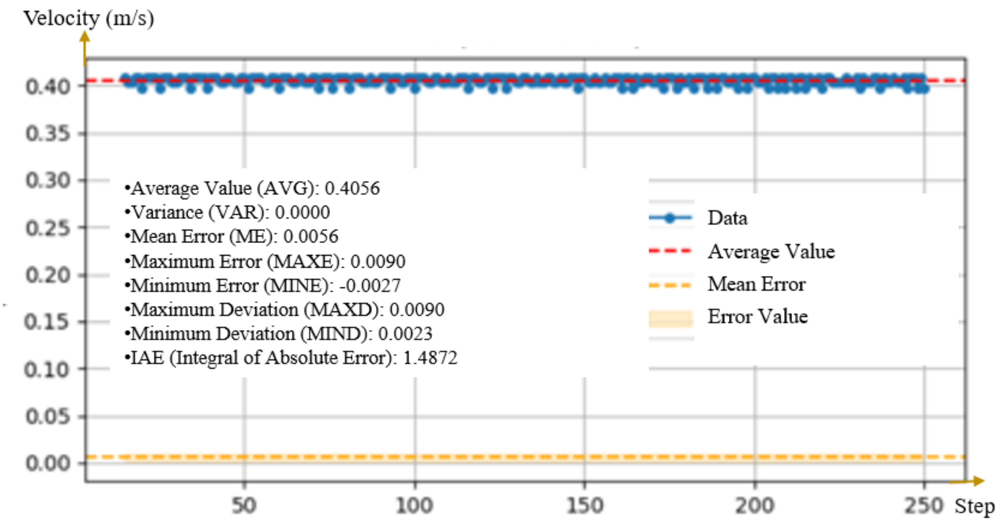

Figure 5. System Response with PID at 15-236 Steps and steady-state parameters

The response graph of the PID system without Kalman filter. The number of steps from 0 to 15. Examination of the iteration steps from the initial value of 0 to the target value demonstrates the stability of the PID system, as evidenced by the graph's close alignment with the desired outcome. Deviations from the target are observed at steps 9, 11, 12, 14, and 15, with the system reaching the target value at step 6. The response graph depicted in Figure 5 represents the PID system's stable state from steps 15 to 236. An average value of 0.4056 is observed, corresponding to a mean error of 0.0056. These metrics indicate that the system has successfully stabilized and attained the desired value with minimal variance from the target, suggesting good tuned of the system parameters.

3.2 PID system combined with Kalman filter

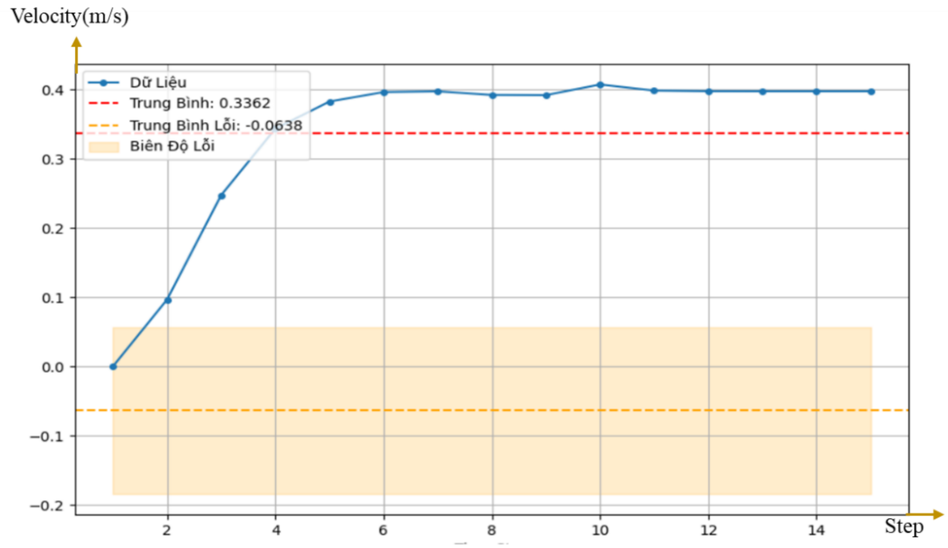

Figure 6. System Response with KALMAN-PID at the First 15 Steps

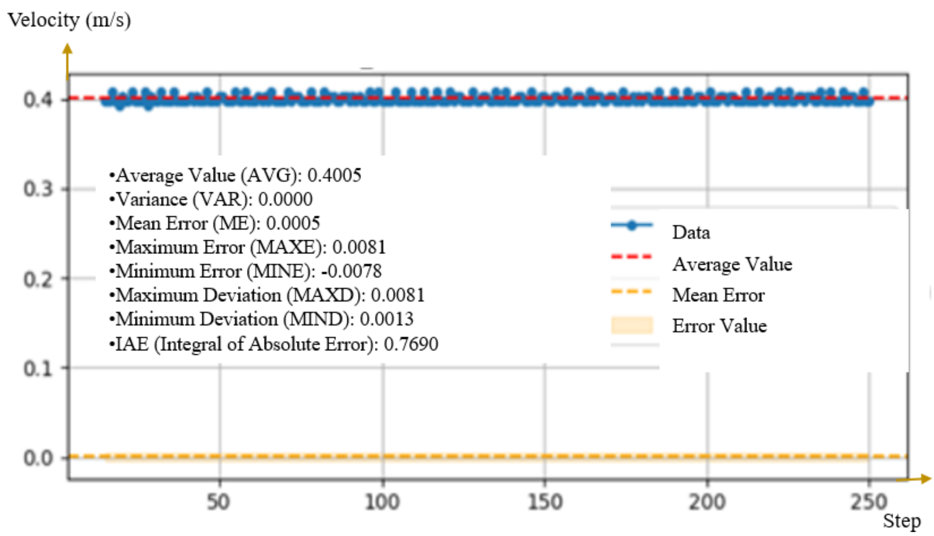

Figure 7. System Response with KALMAN-PID at 15-236 Steps and steady -state parameters

The response graph of the PID system combined with Kalman filter. The number of steps from 0 to 15. Examination of each iteration step from 0 to the target value indicates the PID system's stability in figure 6. Deviations from the target occur at steps 8, 9, and 10, with the target value attained at step 6. The incorporation of a Kalman filter does not substantially impact the time required to reach the target function from system initiation.

The response of the PID system integrated with a Kalman filter is depicted in Figure 6. Step count ranges from 15 to 236. The same PID parameters. An average value of 0.4005 is observed, corresponding to a mean error of 0.0005. These values indicate that the system has successfully stabilized and attained the optimal system respond.

3.3 Analysis:

Table 1. Summary of PID and kalman-PID Parameters

Type of control	Test Parameters						
	Average	**Mean Error**	**Max Error**	**Min Error**	**Max Deviation**	**Min Deviation**	**IAE**
PID	0.4056	0.0056	0.0090	-0.0027	0.0090	0.0023	1.1872
KALMAN-PID	0.4005	0.0005	0.0081	-0.0078	0.0081	0.0013	0.7690

In table 1 shows clear performance PID and combined Kalman_PID. The experimental results reveal differences between the PID and Kalman-PID control systems. The average control variable value during testing was 0.4056 for PID and 0.4005 for Kalman-PID, with the latter demonstrating superior accuracy by more closely approximating the target. In terms of mean error, Kalman-PID (0.0005) substantially outperformed PID (0.0056), showcasing its efficacy in mitigating noise.

Maximum error observations further underscore Kalman-PID's advantages, with values of 0.0081 compared to PID's 0.0090, suggesting enhanced stability under high-noise conditions. Minimum error data, however, presents a more nuanced picture: PID at -0.0027 versus Kalman-PID at -0.0078. While Kalman-PID's more negative value might indicate faster responsiveness, this aspect requires careful consideration in specific applications. Examining deviations from the target value, Kalman-PID again demonstrates superiority. Maximum deviations were 0.0081 for Kalman-PID and 0.0090 for PID, while minimum deviations were 0.0013 and 0.0023, respectively. These results indicate Kalman-PID's improved system stability and control performance.

The Integral of Absolute Error (IAE), a comprehensive performance metric where lower values signify better control, further validates Kalman-PID's effectiveness. Kalman-PID achieved an IAE of 0.7690, substantially lower than PID's 1.1872, demonstrating superior overall error reduction capabilities..

4. CONCLUSION

The integration of the Kalman filter into the control system substantially mitigates the impact of measurement noise, thereby enhancing speed control precision and reducing system oscillations during startup by 40%, from five oscillation steps to three. Additionally, the oscillation amplitude is decreased by an impressive 91.07%. The observed reduction in the Integral of Absolute Error (IAE) within the Kalman-PID system signifies more effective error minimization over time. Experimental data further corroborate that the Kalman filter efficiently eliminates undesirable encoder signal noise while maintaining the system’s response time, thus improving overall system stability and performance. However, achieving optimal performance with the Kalman filter necessitates meticulous tuning of its parameters. This tuning process can be intricate and time-intensive, particularly in real-time embedded systems where computational resources are constrained.

Inadequate configuration may lead to delayed system responses or instability. Consequently, a trade-off often exists between noise reduction and responsiveness, highlighting the importance of developing adaptive or automated tuning strategies suitable for real-time applications. To gain a deeper understanding of the robustness of the Kalman-PID controller, future research should investigate its behavior under various operating conditions, including fluctuating load scenarios and environments characterized by non-Gaussian noise. These studies will provide valuable insights into the filter's adaptability and efficacy in real-world conditions. In conclusion, while the Kalman-PID system exhibits significant potential in enhancing DC motor control by mitigating measurement noise and improving stability, further research is necessary to address tuning complexity and ensure consistent performance across diverse industrial applications. Extended stability analyses and validation across different operational profiles will contribute to the broader adoption of the Kalman-PID strategy in modern automation and robotics systems.

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PHÂN TÍCH HIỆU QUẢ LÝ THUYẾT VÀ THỰC NGHIỆM CỦA VIỆC KẾT HỢP BỘ LỌC KALMAN VÀ PID TRONG ĐIỀU KHIỂN TỐC ĐỘ ĐỘNG CƠ DC

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TỪ KHOÁ

Lọc Kalman ;
PID;
K_PID;
IAE.

TÓM TẮT

Bộ điều khiển Tỷ lệ – Tích phân – Vi phân (PID) là một phương pháp điều khiển tự động được sử dụng rộng rãi trong nhiều lĩnh vực. Nhiều phương pháp tinh chỉnh đã được phát triển để đạt được hiệu suất tối ưu cho các hệ thống điều khiển PID. Bài báo này trình bày việc thiết kế một hệ thống điều khiển PID kết hợp với bộ lọc Kalman, có khả năng duy trì hiệu suất tối ưu cho động cơ DC dựa trên tiêu chí Tích phân của Sai số Tuyệt đối (IAE). Giá trị IAE đối với PID cổ điển là 1.1872, trong khi giá trị IAE đối với hệ thống kết hợp (bộ lọc Kalman tích hợp với bộ điều khiển PID – K_PID) là 0.769. Kết quả thực nghiệm chứng minh rằng việc tích hợp bộ lọc Kalman đã cải thiện đáng kể hiệu suất của bộ điều khiển PID, đặc biệt trong việc giảm thiểu tác động của nhiễu.