An Unmanned Forklift Steering Control System Utilizing IoT and PID with a Kalman Filter for Enhanced Stability and Precision

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ABSTRACT

This study focuses on developing an unmanned forklift steering control system utilizing the Internet of Things (IoT) for remote operations. The objective was to integrate a Proportional Integral Derivative (PID) control system to accurately measure the rotation speed and angular position of the steering wheel. Sensor data is refined using the Kalman Filter technique (KF), which effectively reduces noise and improves the accuracy of steering angle data, leading to smoother and more stable steering control during forklift turns. This study utilizes a rear-wheel steering configuration for autonomous control via microcontrollers and IoT-based remote operation systems. Kinematic analysis governs motion and steering by calculating the Instantaneous Center of Rotation (ICR) based on the vehicle's linear and angular velocities. A limit switch facilitates accurate angular position tracking and ensures system consistency for steering wheel homing. The feedback control system employs a wheel encoder and gyroscopic sensors with a PID controller to maintain precise steering through motor speed adjustments that correct errors. Experimental results demonstrate the ability of the control system to accurately adjust and follow the desired trajectory. Initially, during the turning phase, the vehicle may not adjust its direction in time, but the control system subsequently adjusts to ensure accurate path following. The angular error is high when the vehicle reaches a 90-degree corner but decreases to near zero as it moves along the straight path, indicating effective alignment with the desired direction. Control input shows linear velocity decreases near corners for smoother turns and increases on straight paths, while turning rate is high at corners and decreases on straight paths, reflecting precise steering response. Lateral error increases during turns but decreases to near zero on straight paths, demonstrating the control system's ability to maintain proximity to the desired path.

Keywords-unmanned forklift; IoT; PID control; Kalman filter; steering control; enhanced stability

I. INTRODUCTION

Currently, Internet of Things (IoT) technology plays a pivotal role in industrial sectors by enhancing operational efficiency through real-time data transmission and remote machinery control. In the field of autonomous navigation, as highlighted in recent studies, the precision of steering response and bearing angle control is paramount for operational safety [1]. Although standard Proportional-Integral-Derivative (PID) control is widely used, it often struggles with sensor noise and signal latency in industrial environments. This research advances beyond the existing literature by proposing a synergistic integration of PID and a standard Kalman Filter (KF). The choice of a standard KF, as opposed to more complex variants such as EKF or UKF, is justified by its superior computational efficiency on the ESP32 platform, providing the low-latency sensor fusion required for real-time applications. This integrated framework specifically addresses high-frequency mechanical vibrations and communication jitter, ensuring a level of precision that standalone controllers cannot maintain. Furthermore, wireless monitoring frameworks can improve industrial performance by up to 30% through predictive maintenance [2].

The integration of IoT in mechanical automation not only improves detection accuracy but also optimizes production throughput. Forklifts, as essential material handling equipment, require precise control to maintain safety and productivity in warehouse environments [3-5]. Recent advances have introduced fuzzy logic and IoT-enabled scheduling to manage the remaining useful life of cooperating forklifts, ensuring long-term reliability [6]. Moreover, the development of autonomous control methods using deep learning for object detection has significantly enhanced the loading and unloading capabilities of vehicle-mounted equipment [7]. Automated transport processes using industrial forklifts further demonstrate the shift toward fully integrated logistics systems [8], where the Industrial Internet of Things (IIoT) provides the necessary connectivity and real-time analytics to optimize efficiency [9].

To achieve high-precision operation and stability, advanced control strategies, such as PID control, are often integrated with the IoT. PID controllers are highly effective in managing positive systems and hydraulic mechanisms by reducing oscillations and improving stability under external disturbances [10, 11]. For example, tuning the PID parameters is crucial for eliminating load oscillations in crane-like dynamic systems, which directly impacts safety [12]. In motor control applications, PID strategies have shown robust performance in maintaining stable rotational speeds, as demonstrated in autonomous underwater vehicle prototypes [13]. These findings provide a solid foundation for achieving precise steering and propulsion control in forklift systems. Furthermore, optimizing PID models through neural networks and Grey Wolf Optimization (GWO) can significantly enhance stability in complex industrial processes [14].

Data accuracy in these IoT-enabled control systems is often compromised by sensor noise. The implementation of KF algorithms on edge devices has been shown to improve the accuracy of low-cost sensors for environmental and vehicular monitoring [15]. Furthermore, recent studies, such as [16], have demonstrated the effectiveness of KF in optimizing kinematic accuracy for navigation systems and estimating trajectories for remotely operated vehicles. In vehicular state estimation, holistic KF design frameworks that consider the observability and dominance properties of measurands are vital for maintaining stability in dynamic environments [17].

Despite these advances in IoT and control strategies, achieving a balance between high-precision maneuvering and system stability in unmanned forklifts remains a challenge, particularly under sensor noise interference in dynamic warehouse environments. Existing studies often overlook the integration of real-time IoT monitoring with robust noise-filtering control for rear-wheel steering configurations. Therefore, there is a need for a dedicated system that combines PID control with Kalman filtering to ensure reliable steering performance.

This research focuses on the development of a forklift control system using IoT technology to enhance the efficiency of remote operation. By implementing a PID control system, the rotational speed and angular position of the steering wheel are measured with high precision. Sensor data is processed using the KF technique, which effectively reduces noise and increases the accuracy of steering angle data. As a result, the steering control becomes smoother and more stable, ensuring dynamic balance and significantly enhancing steering stability during forklift maneuvers. The integration of IoT not only improves operational efficiency but also elevates safety standards in industrial environments.

II. MATERIALS AND METHODS

A. *Forklift Structure*

The forklift in Figure 1 has a total weight of 2,400 kg. The vertical distance from the wheels to the top of the mast is 2,500 mm. When fully extended, the lift reaches a maximum height of 4,000 mm. The forklift's width is 1,200 mm, the body length is 2,000 mm, and the fork length is 1,500 mm.

The braking system is equipped with a DC linear motor, as illustrated in Figure 2(a), since the forklift must engage the brake before movement. Additionally, a linear stepper motor is mounted on the accelerator to control the vehicle's forward and reverse speeds, as shown in Figure 2(b).

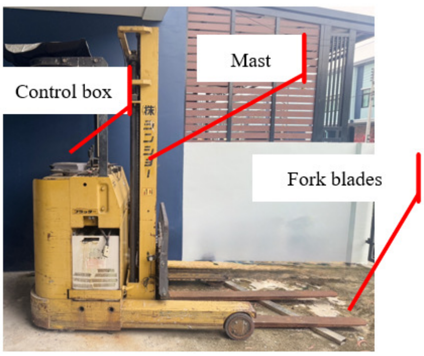


Fig. 1. Forklift machine.

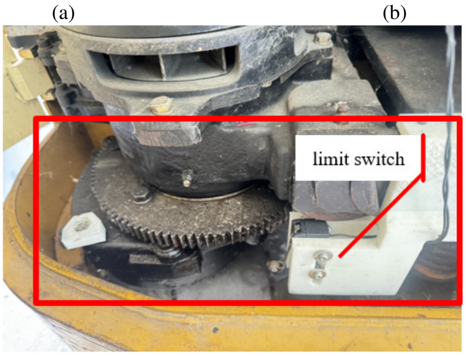
(a) (b)

Fig. 2. Low-level control: (a) brake, (b) accelerator.

B. *Steering Control*

Figure 3(a) shows the steering wheel. An incremental rotary encoder, shown in Figure 3(b), with 360 Pulses Per Revolution (360 PPR), is used to measure the angular position of the steering system. This provides a resolution of 1° per pulse, enabling precise control of the steering angle when used in conjunction with PID algorithms. The 12/24 VDC gear motor has a rated speed of 1500 RPM and a power of 18.5 W. It is connected to a gear system with a 10:1 reduction ratio, resulting in an output speed of 150 RPM. This setup significantly increases torque, making it suitable for autonomous forklift steering control, as shown in Figure 3(c). A limit switch is installed to serve as the home position reference. When the wheel rotates and contacts the limit switch, the encoder begins reading the angular position. The system then commands the motor to return to the predefined home position, which serves as the standard reference for all subsequent steering control operations.

(a) (b)



(c)

Fig. 3. Steering control: (a) direction control, (b) DC gear motor, (c) limit switch.

To provide a clearer understanding of the mechanical assembly, an exploded view is presented in Figure 3(b). This view illustrates the coaxial alignment between the steering gear motor and the incremental rotary encoder. The encoder is coupled directly to the rear shaft of the motor, ensuring that every fractional rotation of the steering gear is captured with high precision. This mechanical synchronization is critical for providing the real-time angular feedback required by the KF and the PID control loop.

When the steering wheel is fully rotated by 360°, the forklift's wheels turn 180°. On the other hand, when turning right, the steering wheel moves in the opposite direction. After successfully testing the steering wheel and wheel movements, the results are calculated to determine the signal required to operate the DC motor for controlling turns at various angles, as shown in Figure 4.

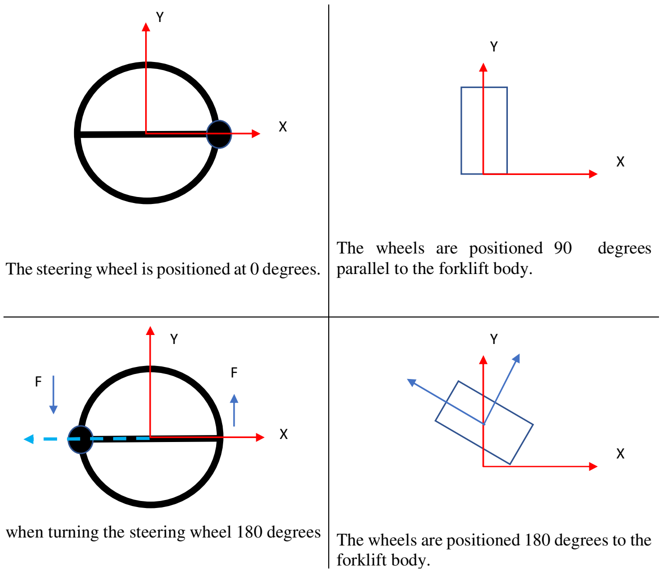


Fig. 4. Angle of steering.

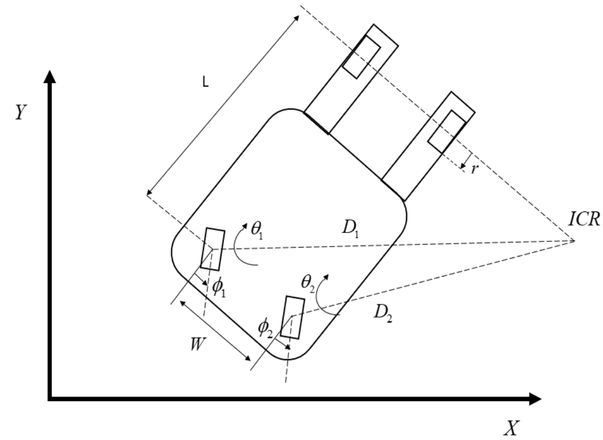


Fig. 5. Forklift head angle control.

C. Control System Design for a Rear-Wheel Steering Forklift

A rear-wheel steering forklift configuration is implemented due to its high maneuverability and suitability for confined environments such as warehouses. The vehicle uses front wheels for driving and a single rear wheel for steering. This setup is particularly effective for autonomous control via microcontrollers and is compatible with IoT-based remote operation systems, as shown in Figure 5.

1) Kinematic Analysis

Kinematic analysis is employed to accurately control the motion and steering of the unmanned forklift. The analysis is based on the vehicle's linear velocity v and angular velocity ω, from which the Instantaneous Center of Rotation (ICR) can be calculated:

$$ICR = \begin{cases} -\frac{v}{\omega} & \omega \neq 0 \\ \infty & \omega = 0 \end{cases} \tag{1}$$

The ICR determines the rear wheel steering angle, which is controlled by a DC gear motor equipped with a 360-pulse-per-revolution encoder. This allows the steering wheel to be rotated precisely according to the desired trajectory.

2) Homing Procedure

A limit switch is installed to define the initial (home) position of the rear steering wheel. When the wheel contacts the switch, the encoder pulse count is reset to zero. This ensures accurate angular position tracking and consistency across system restarts.

3) Rear Wheel Steering Angle Calculation

Based on the ICR, the left and right rear steering angles can be determined using:

$$\begin{bmatrix} \omega_1 \\ \omega_2 \end{bmatrix} = \begin{cases} \begin{bmatrix} -a\tan 2\,(L, ICR + \frac{W}{2}) \\ -a\tan 2\,(L, ICR - \frac{W}{2}) \end{bmatrix} & ICR \geq 0 \\ \begin{bmatrix} \pi - a\tan 2\,(L, ICR + \frac{W}{2}) \\ \pi - a\tan 2\,(L, ICR - \frac{W}{2}) \end{bmatrix} & ICR < 0 \end{cases} \tag{2}$$

where L is the wheelbase (distance between front and rear axle), and W is the vehicle track width (distance between left and right wheels).

4) Angular Velocity of Rear Wheel

The required angular velocity of the steering wheel ($\dot{\theta}_1$, $\dot{\theta}_2$) can be calculated as:

$$\begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \end{bmatrix} = \begin{cases} -\begin{bmatrix} \frac{D_1\omega}{r} \\ \frac{D_2\omega}{r} \end{bmatrix} & ICR \geq 0 \\ \begin{bmatrix} \frac{D_1\omega}{r} \\ \frac{D_2\omega}{r} \end{bmatrix} & ICR\langle 0 \end{cases} \tag{3}$$

where D_1 and D_2 are distances from each wheel to the ICR, and r is the radius of the wheel.

The kinematic model of the unmanned forklift is defined by (1)-(3). To ensure consistency with the physical structure, all spatial variables are measured in millimeters (mm).

5) Feedback Control System

The system uses PID control based on feedback from the wheel encoder and gyroscopic sensors to maintain precise steering. The encoder provides real-time angle data, while the gyro tracks the angular deviation. To enhance the accuracy and reliability of these sensor measurements, particularly in the presence of noise, a KF technique is applied. The KF fuses the noisy sensor readings from the encoder and gyroscope to produce optimal estimates of the steering angle and angular velocity, effectively reducing measurement noise and providing a more accurate state estimation for the PID controller. The PID controller continuously adjusts the motor speed to correct errors, minimize overshoot or undershoot, and ensure that the wheel returns to the setpoint efficiently, maintaining a smooth and stable turning.

The PID controller parameters for the steering system were determined using the Ziegler-Nichols tuning method, which involved identifying the ultimate gain (K_u) and oscillation period (P_u) under closed-loop control. Following the initial calculation, fine-tuning was performed during experimental trials to minimize overshoot and settling time. The final optimized gain values used in this study are K_P = 12.5, K_i= 0.05, and K_d = 2.1. Using these parameters, the forklift's steering response is both stable and reactive within the constrained testing area.

6) Kalman Filter (KF) for Enhanced Prediction Accuracy

The KF algorithm is a central component, used to significantly improve the accuracy of low-cost sensors by 27% through combining observations with error correction. In the context of a forklift, KF could be applied to sensor fusion (e.g., combining data from encoders such as IMUs and GPS) to obtain highly accurate estimates of its position, orientation, and velocity, even with noisy or low-cost sensors. This improved state estimation is vital for precise steering control. The state estimate at the current time step (k) based on the previous time step's state ($k-1$) is predicted using:

$$\hat{x}_k^{\,-} = A\hat{x}_{k-1} + Bu_{k-1} \tag{4}$$

The associated uncertainty (covariance) is predicted using :

$$\hat{P}_k^{\,-} = AP_{k-1}A^T + Q \tag{5}$$

where $\hat{x}_k^{\,-}$ is the predicted state vector at time k, $\hat{x}_{k-1}$ is the estimated state vector at time $k-1$, A is the state transition matrix, B is the control input matrix, u_{k-1} is the control input vector at time $k-1$, $\hat{P}_k^{\,-}$ is the predicted state covariance matrix at time k, P_{k-1} is the estimated state covariance matrix at time $k-1$, and Q is the process noise covariance matrix.

The Kalman Gain (K_k) determines how much the prediction should be corrected based on the new measurement, following:

$$K_k = P_k^{\,-}H^T(HP_k^{\,-}H^T + R)^{-1} \tag{6}$$

The state estimate is updated using the new measurement (z_k):

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \tag{7}$$

The updated covariance is calculated using:

$$P_k = (I - K_k H) P_k^- \quad (8)$$

where K_k is the Kalman gain at time k, H is the measurement matrix (relates state to measurement), R is the measurement noise covariance matrix, z_k is the measurement vector at time k (from encoder and gyroscope), $\hat{x}_k$ is the updated state vector at time k, P_k is the updated state covariance matrix at time k, and I is the identity matrix.

In this context, the state vector $\hat{x}$ would typically include the steering angle and angular velocity, while z would be the noisy readings from the encoder and gyroscope. The KF uses these equations to provide a more accurate and smoothed estimate of the true steering angle and angular velocity to the PID controller.

D. Circuit Connection and IoT User Interface for Forklift Control

1) Circuit Connection

Figure 6 shows a sketch diagram of the circuit connected to various parts. The circuit control architecture is built around the ESP32 microcontroller. The system is powered by a 12V battery, which is regulated through a step-down buck converter to provide a stable 5V and 3.3V supply for electronics. The ESP32 interfaces with the BTS7960 High-Current Motor Driver to manage the 12V DC gear motor for steering. Precise feedback is maintained through an incremental encoder connected to the motor shaft, while a limit switch is integrated at the steering column to facilitate the 'homing' procedure for absolute zero-position calibration. This configuration ensures that the microcontroller can execute high-frequency PID calculations based on real-time hardware feedback.

2) IoT System

The Forklift-IoT interface is designed for remote control and monitoring of a forklift through an IoT system. This interface features clear control elements. It displays real-time monitoring data such as "Compass Heading: N/A" and "Encoder Position: N/A," which are crucial for precise and stable steering control. The "Forklift Movement Controls" include buttons for "Forward," "Home," and "Reverse" for basic movement, along with "Turn Left," "Turn Stop," and "Turn Right" for steering. In addition, "Brake Forward," "Brake Stop," and "Brake Reverse" manage braking during various movements. A "Motor Speed: 50%" slider allows users to adjust the forklift's speed. Finally, "Start Recording" and "Stop Recording" buttons manage data logging for analysis, with an "Open Data" button providing access to recorded information, likely in an Excel file. Overall, this interface demonstrates a comprehensive remote control capability for an unmanned forklift, leveraging IoT for real-time monitoring and command execution to enhance operational efficiency and safety in industrial environments, as shown in Figure 7.

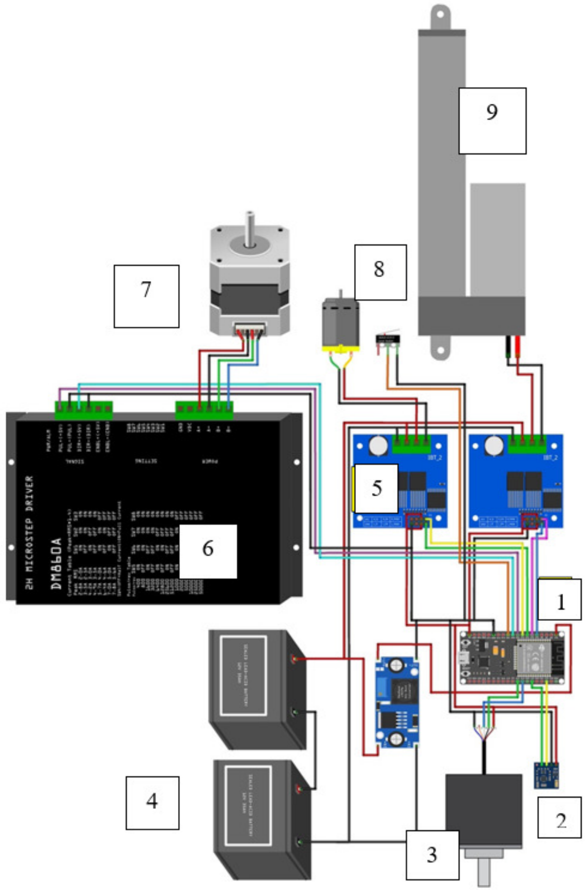


Fig. 6. Circuit control: 1. ESP32 board, 2. Compass sensor, 3. Sensor encoder, 4. Battery, 5. Driver controlling the DC steering motor, 6. Driver controlling the stepping motor of the accelerator, 7. Stepping motor, 8. DC steering motor, and 9. DC brake motor

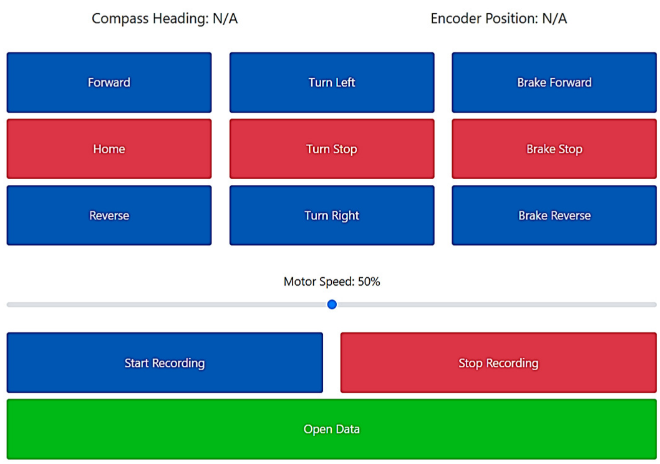


Fig. 7. IoT system.

Table I summarizes the four main components involved in the intelligent forklift control system. Firebase acts as the cloud-based backend that is responsible for storing commands and sensor data through its Realtime Database and REST API. Anto.io functions as the MQTT broker, enabling the system to send and receive commands instantly using the MQTT protocol. At the hardware level, ESP32 serves as the central microcontroller that physically controls the forklift, with dual connectivity to both Firebase and Anto.io for synchronized operation. Finally, the Web App, developed using HTML and JavaScript, provides an intuitive user interface that connects to both Firebase and Anto.io, allowing users to remotely monitor and control the forklift's behavior in real-time.

TABLE I. IOT FORKLIFT SYSTEM

System	Function	Connection method
Firebase	Stores commands and sensor data	Realtime Database / REST API
Anto.io	Sends and receives MQTT commands	MQTT Protocol
ESP32	Controls the forklift	Connects to both Firebase and MQTT (Anto.io)
Web App	User control interface	Built with HTML/JS, connected to Firebase & Anto.io

III. RESULTS AND DISCUSSION

The control system was evaluated in a 10×10 m rectangular area, with real-time telemetry data logged via the IoT framework for subsequent analysis. As shown in Figure 8, the forklift follows a predefined trajectory (red dashed line). During the initial turning phases, a transient response delay was observed—primarily due to mechanical inertia and communication latency. However, the integrated PID-KF control loop effectively compensated for these deviations, steering the vehicle (blue solid line) back to the reference path with high precision as the system attained steady-state stability.

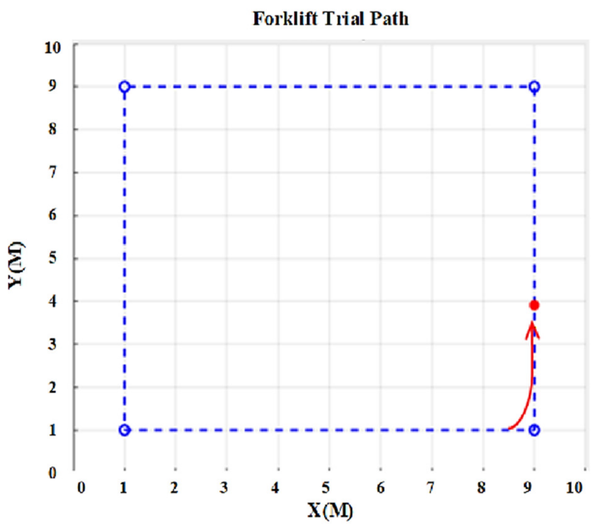


Fig. 8. Square desired trajectory.

Figure 9 shows the orientation error. At the beginning, when the vehicle reaches the 90-degree corner of the rectangle, the angular error is high because the vehicle has not yet turned in the direction of the path. As the vehicle moves along the straight path, the angular error decreases and adjusts to a value close to zero. The decrease in the graph indicates that the control system can better align the vehicle's direction with the path over time.

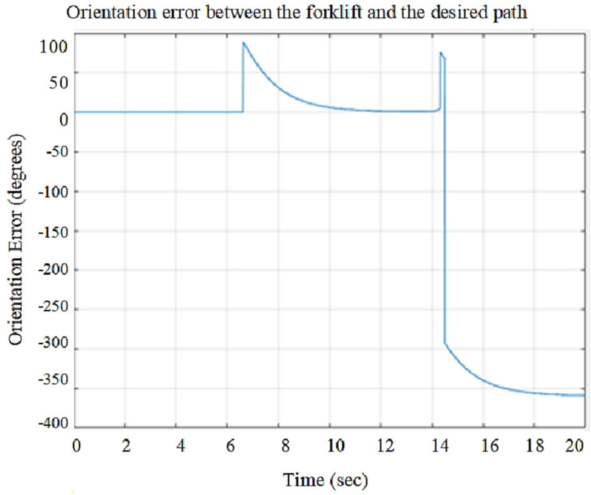


Fig. 9. Orientation error.

The experimental results confirm that a standard PID control loop (Baseline), while capable of tracking the target, struggles with high-frequency feedback noise typical in rear-wheel steering forklifts, leading to an RMSE of 2.42°. This jittery response can cause mechanical wear and reduced path accuracy. By integrating the KF (Proposed), the feedback signal is refined before entering the PID loop. As shown in Figure 10 and Table II, this integration effectively dampens oscillations, reducing the peak error by 70.6% and ensuring a smoother, more stable steering trajectory.

TABLE II. QUANTITATIVE PERFORMANCE COMPARISON BETWEEN PID AND PID+KF CONTROL

Performance metric	Baseline (PID)	Proposed (PID + KF)	Improvement (%)
RMSE (degrees)	2.42°	0.68°	71.9%
Peak error (Max deviation)	4.15°	1.22°	70.6%
Standard Deviation (σ)	1.85°	0.42°	77.3%

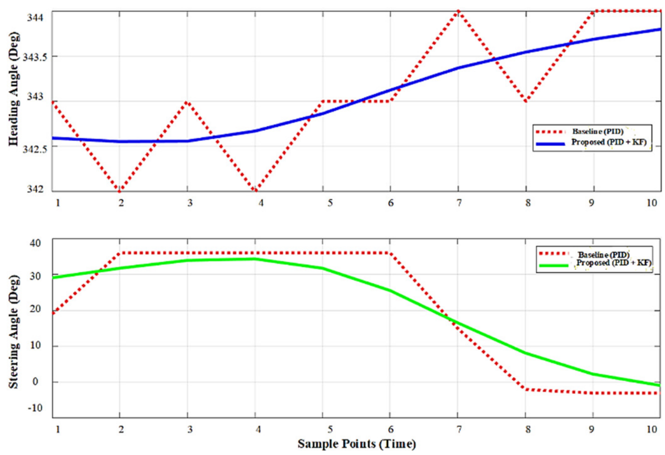


Fig. 10. System response comparison.

In the initial phase, u_1 (linear velocity) will increase to quickly bring the vehicle onto the path. However, as it approaches the corner, the speed will decrease in preparation for the turn. Meanwhile, u_2 (turning rate) will show significant changes when the vehicle needs to turn at a 90-degree angle. The value of u_2 will be high when reaching the corner of the rectangle and will decrease when moving along the straight path, as shown in Figure 11.

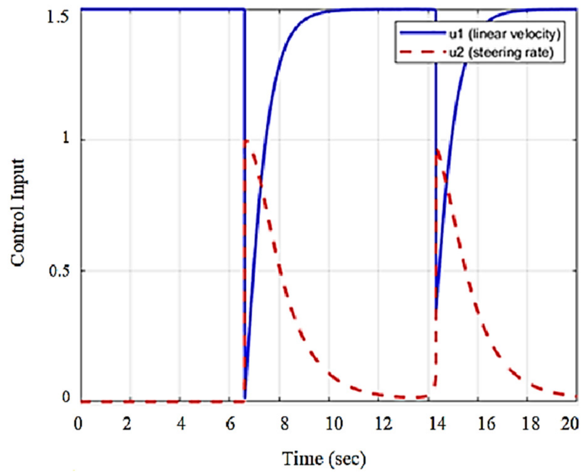


Fig. 11. Control inputs and u_1 and u_2.

The lateral error indicates how far the vehicle is from the desired path. In the case of turning at a corner, the lateral error increases because the vehicle takes time to adjust its direction. However, once the vehicle moves straight along the path, the lateral error decreases to near zero. The control system helps reduce this error value to keep the vehicle as close to the desired path as possible, as shown in Figure 12.

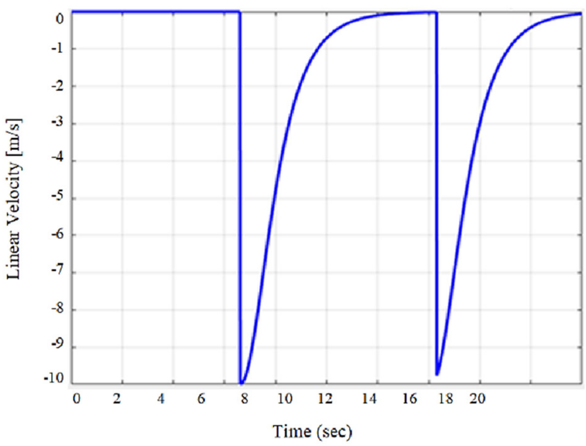


Fig. 12. Lateral error between the forklift and the desired path.

In Figure 13, in the initial phase, the speed will increase to accelerate the vehicle onto the path. However, as it approaches the corner of the rectangle, the speed will clearly decrease in preparation for the turn, allowing for a smoother maneuver. After that, the speed will increase again as the vehicle moves along the straight path.

As shown in Figure 14, the turning rate will increase rapidly when the vehicle needs to turn at the corners of the rectangle and decrease when the vehicle moves along the straight path. This change reflects the steering system's response to sharp turns. Once the turn is completed, the turning rate will return to a low and stable value when moving along the straight path.

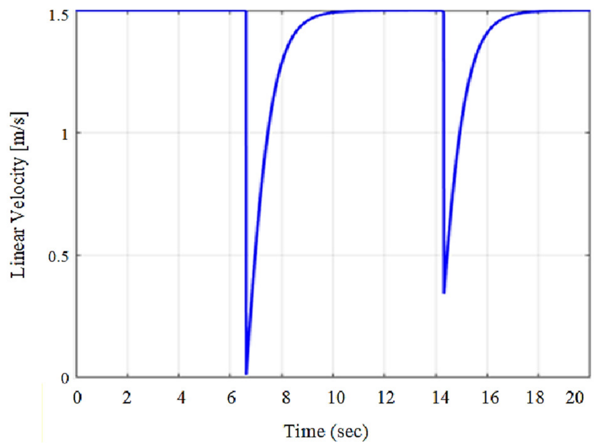


Fig. 13. Linear velocity v_d of the steering wheel.

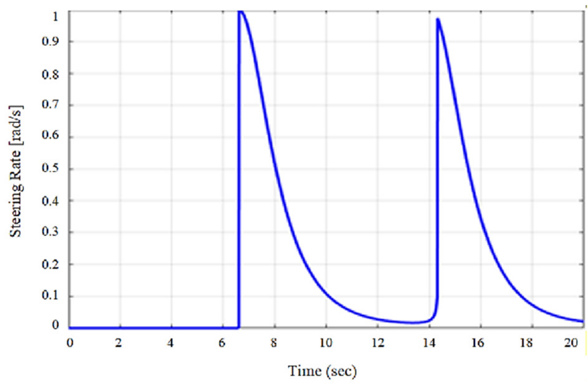


Fig. 14. Steering rate ω_d.

IV. CONCLUSION

This research developed an unmanned forklift steering control system that significantly enhances operational efficiency, stability, and precision through the integration of IoT technology, PID control, and a KF. The system precisely measures the rotational speed and angular position of the steering wheel using a PID control system, with sensor data processed by a KF to reduce noise and improve accuracy. The comparative analysis demonstrated that the proposed PID+KF integration significantly outperforms the baseline PID controller, achieving a 71.9% reduction in RMSE and a 70.6% reduction in peak error during 90-degree turns. This leads to smoother and more stable steering control, particularly in high-maneuverability rear-wheel steering configurations suitable for confined environments.

The feedback control system, built around an ESP32 microcontroller, effectively utilizes data from an encoder and gyroscope to manage angular velocity and steering angle. By implementing the KF as a pre-processing stage, the standard deviation of steering feedback was reduced to 0.42°, ensuring that the PID controller could minimize overshoot and undershoot more effectively. Experimental tests conducted on a 10×10 meter rectangular path confirmed the system's ability to accurately follow the desired trajectory with minimal lateral error. Quantitative metrics show that once the forklift transitioned to a straight path, the lateral error was reduced to near zero, validating the robustness of the control logic. These results collectively affirm that integrating IoT with PID control and Kalman filtering provides a robust, high-precision solution to the operational demands of unmanned industrial vehicles.

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