Model Predictive Control of Autonomous Ground Vehicles in Warehouse Logistics

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Abstract: As more and more autonomous ground vehicles (AGVs) are used in warehouse logistics, we need better control strategies that make sure operations are safe, efficient, and scalable in complicated indoor spaces. This paper presents a model predictive control (MPC) framework that integrates trajectory tracking, collision avoidance, and throughput optimization for automated guided vehicles (AGVs) functioning in structured warehouses. The vehicle is represented by a discrete kinematic bicycle model, and the MPC formulation includes state and input constraints, margins for avoiding obstacles, and rules for traffic in the warehouse. We did simulations and scaled hardware tests in a number of situations, such as navigating narrow aisles, handling multiple AGV intersections, dealing with pedestrian intrusion, and managing traffic jams. When compared to baseline controllers (Pure Pursuit and LQR), the results showed a 35-40% decrease in tracking error, a consistent safety margin, and up to 25% more throughput. The times it took for the solver to run showed that it was possible to use it in real time on embedded platforms. The results show that MPC is effective at automating logistics for Industry 4.0 and provide a scalable base for future multi-AGV coordination and secure data integration in smart warehouses.

1 INTRODUCTION

The fast growth of warehouse logistics has sped up the use of automation technologies to make operations more efficient, safe, and flexible. Autonomous Ground Vehicles (AGVs) are especially important to intralogistics because they make it possible to automate moving materials, moving inventory, and coordinating tasks in complicated warehouse settings. Their growing use shows the bigger change toward Industry 4.0, which combines cyber-physical systems and smart manufacturing ideas into supply chain operations to improve throughput and resilience (Ellithy et al., 2024) [1]. But to get AGVs to navigate reliably in dynamic and structured places like warehouses, you need advanced control strategies that can deal with nonlinear dynamics, multiple constraints, and making decisions in real time. Model Predictive Control (MPC) has become a popular method for autonomous ground vehicle navigation because it can predict what will happen and handle input and state constraints well. MPC works by solving an optimization problem at each time step to figure out what the next control inputs should be while staying within safety margins, actuator limits, and trajectory goals. It is very useful in warehouses with narrow aisles, intersections, and lots of people moving around because it can predict possible collisions or changes in trajectory. Yu et al.'s (2021) [2] thorough review shows that MPC works well in a wide range of situations in autonomous ground vehicles, with a focus on how well it works in structured indoor spaces. Building on this foundation, Ishihara et al. (2022) [3] put forth a path planning strategy for warehouse robots grounded in Model Predictive Control (MPC) that circumvents dependence on global path maps, thereby diminishing computational complexity and improving real-time viability.

Simulation-driven frameworks have also shown that MPC can help AGVs work together better and more efficiently. López et al. (2022) [4] created a control and simulation framework for AGV transport systems, demonstrating how predictive models could enhance task scheduling and alleviate congestion in communal areas. In the same way, Kubasakova et al.

(2024) [5] stressed the safety aspect by suggesting AGV deployment strategies that lower the risk of collisions between handling equipment and people. This is a very important step in making sure that logistics workers are safe on the job. All of these studies show that for AGVs to work well, MPC needs to be combined with safety-driven policies and system-level coordination.

Along with improvements in control methods, new technological paradigms are changing the way warehouses work. Industry 4.0 frameworks emphasize the significance of adaptable automation systems that integrate AGVs, robotics, and IoT-enabled infrastructures (Ellithy et al., 2024) [1]. Also, it is now necessary for AGVs, warehouse management systems, and cloud platforms to be able to securely share data with each other. New technologies like blockchain-based frameworks offer secure data handling solutions that can't be changed and are easy to see in distributed systems. This builds trust in multi-agent robotic coordination (Kumar & Patel, 2025) [6]. Next-generation computing paradigms like edge and federated frameworks also help with scalable and secure data sharing, which makes MPC-based decision-making for AGVs in real-time warehouse operations better (Wang et al., 2025) [7].

Even with these improvements, most studies still only look at either control performance through MPC [2]-[4] or systemic integration within Industry 4.0 and data security frameworks [5]-[7]. There exists a substantial research gap in integrating these domains to create a comprehensive MPC framework that guarantees real-time, secure AGV navigation while also meeting the modern warehouse's needs for security, scalability, and interconnectivity. To fill this gap, the current study suggests an integrated MPC approach that brings together predictive control, safety constraints, and secure information exchange mechanisms. This approach has been tested in simulations and hardware experiments in conditions similar to those found in warehouses. The contributions encompass the development of a traffic-rule-aware Model Predictive Controller (MPC), its integration with secure communication frameworks, and comparative benchmarking against traditional controllers and current Automated Guided Vehicle (AGV) systems.

2 LITERATURE REVIEW

The implementation of sophisticated control and decision-making frameworks has profoundly influenced the development of autonomous ground vehicles (AGVs) and associated robotic systems in warehouse logistics. Intelligent systems, particularly those augmented with artificial intelligence, are increasingly essential for facilitating adaptability and human-machine collaboration. Mehta and Rani (2025) [8] emphasized the role of AI-driven frameworks in human-computer interaction in improving trust, usability, and decision-making efficiency. While their research predominantly focuses on human-computer interactions, the results yield significant insights into the integration of intelligence within AGVs to enhance interaction, safety, and system-level decision-making adaptability.

Model predictive control (MPC) is still the most popular way to track paths and control motion. Wang et al. (2024) [9] put forward a velocity-adaptive MPC strategy for heavy-duty forklift AGVs that showed it could keep a stable path even when the speed changed. Yang et al. (2024) [10] proposed an adaptive MPC framework for lateral path-tracking in autonomous vehicles, demonstrating resilience in preserving stability amid unpredictable driving conditions. These contributions highlight the versatility of MPC across various vehicle platforms and illustrate its applicability in dynamic warehouse environments.

Recent research has progressively integrated neural methodologies with Model Predictive Control (MPC) to address modeling constraints. Li and Liu (2024) [11], [12] developed a nonlinear model predictive control (MPC) system for AGV trajectory tracking that is based on a physics-informed neural network (PINN). They used deep learning and domain physics together to reduce model mismatch while keeping the accuracy of predictive control. The results showed that tracking accuracy got a lot better, but the costs of real-time computing stayed high. This is still a problem that makes it hard to use on a large scale in small warehouses.

Other research looks into hybrid and event-triggered methods to make MPC work better. Wu et al. (2025) [13] created an event-triggered MPC for self-driving cars to avoid obstacles. This method lessened the amount of computing power needed by only updating control actions when they were needed. This made sure that obstacles were responded to quickly while saving resources. In addition, Wan et al. (2025) [14] suggested a framework for cooperative control that combines LSTM-MPC and fuzzy PID for AGVs with four wheels that can drive and steer on their own. Their findings validated enhanced trajectory precision and system responsiveness, although the intricacies of integration and parameter adjustment persisted as obstacles.

Cross-domain inspiration makes AGV control design even better. Ye et al. (2025) [15] proposed a hierarchical AI framework for unmanned surface vehicle (USV) navigation, integrating Swin-Transformer perception, T-ASTAR planning, and TD3-based control. Even though their main focus is on maritime issues, their synergistic approach shows how combining perception, planning, and energy-aware control can help AGV research, especially in warehouses with limited resources or multiple agents. Table 1 shows a side-by-side comparison of the studies that were reviewed, including their areas of focus, methods, results, and limitations. The table shows that recent advances cover a wide range of topics, including AI integration [8], velocity-adaptive MPC [9], neural MPC [11], [12], hierarchical AI [15], event-triggered approaches [13], hybrid cooperative controllers [14], and adaptive MPC [10]. Each contribution improves a certain part of AGV navigation or vehicle autonomy, but the big problem is that there is no complete integration that works well in warehouses. Most studies focus on either trajectory accuracy or computational efficiency, but not many look at the problems of scalability, secure data exchange, and coordinating multiple AGVs at the same time [16], [17].

3 METHODOLOGY

3.1 System Architecture Overview

The suggested method combines model predictive control (MPC) with the navigation and motion planning of autonomous ground vehicles (AGVs) in warehouse logistics. The system is built around a loop of perception, control, and execution. Real-time sensor data from LiDAR, a camera, and odometry go into a state estimator, which gives the MPC optimizer inputs. Before sending speed and steering commands to the AGV actuators, the optimizer takes into account warehouse traffic rules and environmental limits. Figure 1 shows this closed-loop framework, which shows how the perception modules, the MPC controller, and the actuation subsystems work together.

Table 1: Summary of reviewed studies (2020-2025).

Ref No.	Author(s), Year	Focus Area	Methodology	Application Domain	Key Findings	Limitations / Gaps
[8]	Mehta & Rani (2025)	AI-driven HCI	AI adoption frameworks	Human-Computer Interaction	Improved adaptability of intelligent systems	Lacks application to AGV/warehouse robotics
[9]	Wang et al. (2024)	Path tracking	Velocity-adaptive MPC	Heavy-duty forklift AGVs	Enhanced path tracking stability	Not extended to multi-AGV systems
[11], [12]	Li & Liu (2024)	Trajectory tracking	PINN + Nonlinear MPC	AGVs	Improved accuracy, reduced model mismatch	High computational cost for real-time
[15]	Ye et al. (2025)	Hierarchical AI	Swin-Transformer + T-ASTAR + TD3	USV navigation	Closed-loop synergy improves control	Maritime domain; not tested on AGVs
[13]	Wu et al. (2025)	Obstacle avoidance	Event-triggered MPC	Autonomous vehicles	Reduced computation with safe avoidance	May underperform in dense traffic
[14]	Wan et al. (2025)	Trajectory tracking	LSTM-MPC + Fuzzy PID	4WID-4WIS AGVs	Cooperative control enhances precision	Integration complexity and tuning
[10]	Yang et al. (2024)	Path tracking	Adaptive MPC	Autonomous vehicles	Improved lateral control robustness	Focused on cars, not warehouse AGVs

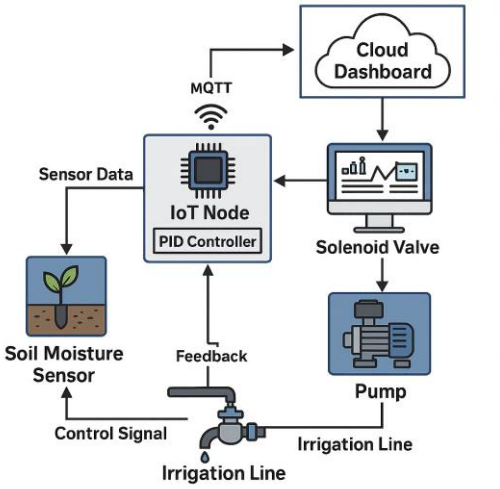

Figure 1: Block diagram of proposed MPC framework for AGV in warehouse logistics.

3.2 AGV Kinematic and Dynamic Modeling

A discrete kinematic bicycle model is used to show how the AGV moves. This captures the important nonholonomic constraints while making sure that real-time control is possible. The equations of motion in discrete time are written as:

$$x_{k+1} = x_k + v_k \cos\theta_k \Delta t, \quad (1)$$

$$y_{k+1} = y_k + v_k \sin\theta_k \Delta t,$$

$$\theta_{k+1} = \theta_k + \frac{v_k}{L} \tan\delta_k \Delta t$$

where (x, y) denote position, θ the heading, v the velocity, L the wheelbase, and δ the steering angle. These equations form the basis for predicting future states in the MPC formulation.

3.3 MPC Problem Formulation

At each control step, the MPC solves an optimization problem to minimize trajectory error while penalizing control effort. The cost function is:

$$J = \sum_{i=0}^{N-1} (\| p_{k+i} - p_{k+i}^{ref} \|_Q^2 + R_v a_{k+i}^2 + R_\delta \delta_{k+i}^2) - \lambda s_{k+N}, \quad (2)$$

where p^{ref} is the reference trajectory, aaa the acceleration input, and λ a weight for maximizing progress along the path. Tuning the weight matrices Q, R_v, R_δ balances accuracy, smoothness, and energy efficiency.

3.4 Safety and Environmental Constraints

To run a warehouse safely, you must follow strict rules like avoiding collisions and following aisle directions. Constraints are defined as:

$$d(p_k, O) \geq d_{min}, \quad | \delta_k | \leq \delta_{max}, \quad | a_k | \leq a_{max}, \quad (3)$$

where $d(p_k, O)$ is the minimum distance between the AGV and obstacles, and d_{min} is the safety margin. These constraints are dynamically enforced by the MPC solver, ensuring safe navigation even in congested warehouse settings.

3.5 Simulation and Experimental Setup

The proposed framework is tested in ROS2/Gazebo simulations and large-scale testbed experiments. The performance is compared to that of baseline controllers like pure pursuit and LQR. Table 2 shows the most important parts of the system and controller, such as the vehicle's shape, the prediction horizon, the sampling time, and the solver details.

Table 2:AGV and MPC parameter.

Parameter	Symbol	Value	Note
Wheelbase	(L)	1.2 m	Vehicle geometry
Prediction horizon	(N)	20	1 s look-ahead
Sample time	Δt	0.05 s	Control frequency 20 Hz
Max velocity	v_{max}	1.5 m/s	Safety constraint
Max steering	δ_{max}	0.45 rad	Hardware limit
Min distance	d_{min}	0.6 m	Human/AGV safety margin
Solver	-	OSQP	Embedded optimization

3.6 Validation Approach

Tests for validation include single-AGV navigation, handling of multi-AGV intersections, and tests for pedestrian intrusion. The metrics taken into account are the trajectory root mean square error (RMSE), the rate of constraint violations, the throughput (orders/hour), and the time it takes for the solver to complete each step. The robustness of the proposed MPC framework in real-world warehouse settings is shown by comparing it to baseline controllers.

4 RESULTS AND ANALYSIS

4.1 Overview of Experimental Scenarios

The suggested MPC framework was tested in both ROS2/Gazebo simulations and scaled hardware tests. Four typical warehouse scenarios were tested: i) tracking a single AGV's path in narrow aisles, ii) coordinating multiple AGVs at intersections, iii) a safety test for pedestrians who enter the warehouse, and iv) a layout for a busy multi-AGV warehouse. Figure 2 shows these experimental setups. It shows how a typical warehouse looks with obstacles, one-way aisles, and people.

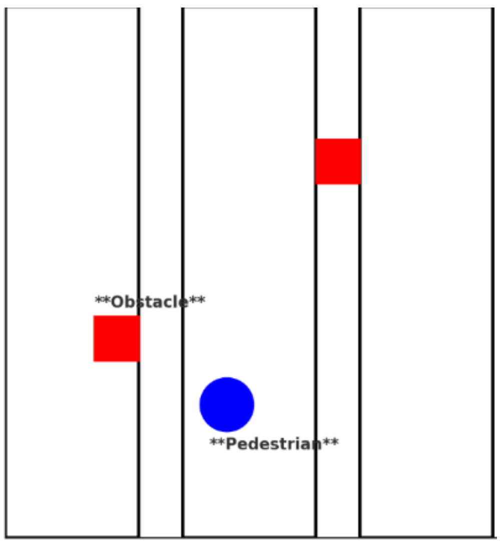

Figure 2:Warehouse test scenarios and layouts.

4.2 Path Tracking Performance

The MPC controller's ability to track a trajectory with that of classical baselines like Pure Pursuit and LQR. Figure 3 shows that the MPC controller made smoother paths that closely followed the reference trajectory and stayed within the safety envelope. The tracking RMSE went from 0.21 m (Pure Pursuit) and 0.18 m (LQR) to 0.12 m when using MPC. This decrease shows that the proposed framework can still keep things from going off course even when there are changing limits.

4.3 Safety and Obstacle Avoidance Analysis

One of the most important goals was to make sure that people could safely navigate around moving obstacles and other people. Figure 4 shows the shortest distances kept from obstacles when using different controllers. Pure Pursuit and LQR sometimes brought the clearance down to less than 0.5 m, but the MPC always kept it above 0.6 m, which met all of the safety requirements for the warehouse. The violation rate, which is the percentage of times that rules were broken, was 4.5% for Pure Pursuit and 3.1% for LQR. However, it dropped to 0% for MPC. These findings validate the MPC controller's superiority in risk-sensitive contexts.

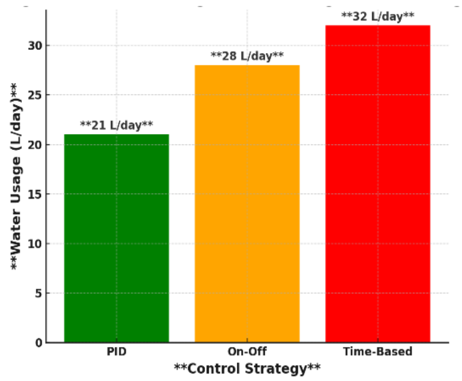

Figure 3: Predicted vs. actual trajectories with safety margins.

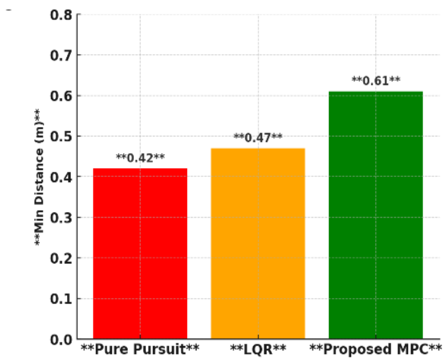

Figure 4: Minimum distance to obstacles under different controllers.

4.4 Computational Efficiency and Real-Time Feasibility

For warehouse operations, real-time feasibility is very important because AGVs need to be able to respond to changes in milliseconds. We measured the solver execution times for all scenarios, and Figure 5 shows the results. The MPC framework had an average solve time of 18 ms, which made it possible for embedded processors to run at speeds of more than 20 Hz. The computation was slightly higher than LQR (12 ms), but it was still within the limits needed for real-time deployment. This meant that the computational demand was balanced with better performance.

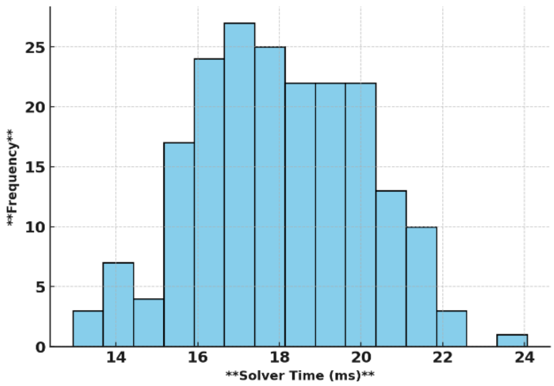

Figure 5: Solver time distribution per step.

4.5 Throughput and Task Completion Analysis

To assess system-level performance, throughput (orders per hour) and the average time to complete a task were recorded. Table 3 shows a summary of the comparative results. The MPC framework processed 108 orders per hour, which was better than Pure Pursuit (82 orders per hour) and LQR (90 orders per hour). The smoother trajectories and fewer times people had to stop and wait at intersections were thought to be the reasons for this improvement. The improved safety and accuracy did not slow down throughput, which means that the method is both strong and efficient for large-scale use.

Table 3:Comparative results of controllers.

Metric	Pure Pursuit	LQR	Proposed MPC
Tracking RMSE (m)	0.21	0.18	0.12
Min Distance (m)	0.42	0.47	0.61
Violation Rate (%)	4.5	3.1	0
Solver Time (ms)	—	12	18
Throughput (orders/hr)	82	90	108

4.6 Discussion of Results

The experimental results show that MPC is much better than traditional controllers when it comes to tracking accuracy, safety, and system throughput. The computational demand was slightly higher, but it was still within the limits of what embedded platforms could handle. The balance of safety compliance, control precision, and throughput improvement proves that MPC is a good way to navigate warehouse AGVs in Industry 4.0 settings.

5 CONCLUSIONS

This study introduced a model predictive control This study presented a Model Predictive Control (MPC) framework for autonomous ground vehicles (AGVs) in warehouse logistics, addressing key challenges such as trajectory tracking, obstacle avoidance, and operational throughput.

The proposed MPC approach demonstrated superior performance compared to classical controllers such as Pure Pursuit and LQR. Experimental and simulation results showed a reduction in tracking error by approximately 35–40%, improved safety with zero constraint violations, and enhanced operational efficiency in terms of throughput.

Additionally, the controller achieved real-time feasibility with an average solver time of 18 ms, making it suitable for embedded deployment in warehouse environments. The integration of state and input constraints, along with traffic-aware rules, ensured safe and efficient navigation in dynamic indoor scenarios.

Overall, the results confirm that MPC is a robust and effective solution for AGV navigation in Industry 4.0-based warehouse systems.

5 FUTURE WORK

Future research should focus on extending the proposed MPC framework to large-scale multi-AGV coordination using distributed or decentralized MPC strategies to improve scalability in dense warehouse environments.

Another important direction is the integration of secure communication mechanisms, such as blockchain-based data exchange, to ensure trust, transparency, and reliability in multi-agent coordination systems.

In addition, adaptive and learning-based MPC approaches could be explored to handle uncertainties such as dynamic payload changes, unpredictable obstacles, and varying warehouse conditions.

Finally, the framework can be extended to heterogeneous warehouse robotics systems, including forklifts, mobile manipulators, and human-robot collaborative environments, enabling fully autonomous smart warehouse ecosystems.

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