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Steady Path: Ensuring Stability in Autonomous Industrial Maneuvering

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Abstract: Autonomous Industrial Vehicles (AIVs) operating in warehouses and industrial facilities must navigate constrained layouts while responding to stationary and moving obstacles. A path that is geometrically collision-free may still produce undesirable motion if vehicle dynamics and terminal behavior are not considered during control. This paper presents SteadyPath, a simulation-based framework for stability-aware autonomous industrial maneuvering. The framework combines a virtual perception layer based on simulator-generated ground-truth object positions and distances, vehicle-state estimation, obstacle-aware decision-making, A* path planning, and Model Predictive Control with terminal constraints. The MPC controller predicts future vehicle motion over a finite horizon and selects steering and longitudinal control actions while seeking a stable terminal condition. The system is evaluated using four scenario tests and a quantitative comparison against a baseline controller. In the reported mission benchmark, the proposed controller completed the mission in 76.4 s compared with 85.6 s for the baseline, reduced mean tracking error from 14.61 m to 2.52 m, reduced peak lateral deviation from 18.91 m to 5.25 m, and increased the clearance buffer margin from 1.30 m to 3.60 m. Both controllers recorded zero dynamic detours or re-plans in the benchmark. The proposed controller was recorded as reaching an invariant stable terminal set, while the baseline was recorded as having a lagging boundary. Scenario testing showed successful outcomes for normal-road, static-obstacle, and fully blocked-road cases; the moving-obstacle case requires clarification because its textual result says the obstacle was handled safely while its status is marked FAIL. The findings indicate improved performance on the reported simulation metrics, while further testing is required to establish robustness across broader dynamic conditions and real sensor inputs.

Keywords: Autonomous Industrial Vehicle, Model Predictive Control, Terminal Constraints, A* Search, Motion Planning, Obstacle Avoidance, Vehicle Stability, Simulation-Based Evaluation.

I. INTRODUCTION

Industrial facilities increasingly use autonomous systems for material movement, internal transport, and repetitive logistics tasks. These environments differ from public roads: aisles may be narrow, turning spaces limited, obstacles may be temporarily placed in travel lanes, and other vehicles or moving equipment may share the same operating area. An autonomous industrial vehicle must therefore do more than find a route from a start point to a destination. It must follow a feasible path, react to changes in the environment, maintain adequate clearance, and avoid abrupt or unstable maneuvers.

Conventional path-search methods, including A*, are useful for finding a route through a represented map. However, a route planner alone does not guarantee that a vehicle can track the route smoothly under its motion constraints. Similarly, a controller that focuses only on short-term tracking may fail to account adequately for the state reached at the end of its prediction horizon. These issues motivate a combined planning-and-control approach in which path generation and vehicle motion regulation are treated as connected stages.

SteadyPath addresses this requirement through a simulation-based navigation pipeline. A virtual perception component obtains obstacle locations and distances from the simulator, and a state-estimation component supplies the vehicle position, velocity, and orientation. A decision-making stage evaluates obstacles and selects safe navigation behavior. A* generates a route, while terminal-constrained MPC computes control actions intended to track the route and guide the vehicle toward a stable terminal condition.

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The contribution of this work is an integrated implementation and evaluation of these modules for autonomous industrial maneuvering. The paper reports scenario outcomes and compares the proposed controller against the baseline model using the values recorded in the project benchmark. It does not claim hardware validation or camera/LiDAR-based perception: the current evaluation uses simulator-provided ground-truth information.

II. LITERATURE SURVEY

The five supplied papers address complementary parts of autonomous navigation: stability-aware obstacle avoidance, uncertainty-aware decision-making, deep-learning perception, layered reinforcement-learning control, and integrated perception-to-motion decision-making. Their methods and limitations provide the basis for positioning SteadyPath.

A. Stability and Terminal-Constraint-Based Obstacle Avoidance

Zhang, Xia, Lu, and Khajepour propose an obstacle-avoidance framework specifically for autonomous industrial vehicles operating in complex scenarios. Their approach considers longitudinal and lateral stability when calculating braking and safety distances, integrates high-level behavioral decision-making with low-level motion tracking, and uses terminal-constraint-based optimization to account for surrounding-vehicle motion. The paper also compares super-twisting sliding-mode control with MPC under different avoidance distances and validates the framework using a hardware-in-the-loop platform. Its central relevance to SteadyPath is the treatment of stability and terminal conditions as part of obstacle avoidance rather than as secondary checks. The present project adopts the stability-focused MPC and terminal-constraint direction in a software simulation workflow, but does not reproduce the paper's complete multidimensional stability model or HIL validation.

B. Robust Decision-Making Through Multi-Modal Fusion and Uncertainty Modeling

Li, Zhang, and Chen introduce a robust decision-making method that combines image and LiDAR features through encoders and attention-based fusion. A fuzzy encoder represents uncertain state information, and a coordination mechanism allows perception and decision-making to exchange feedback. Their reported experiments emphasize robustness in extreme-weather conditions and include ablation studies. This work demonstrates the value of combining complementary sensor modalities and explicitly representing uncertainty. SteadyPath differs in implementation scope: it uses simulator-generated ground-truth positions and distances rather than a camera–LiDAR fusion stack. Consequently, its current evaluation isolates planning and control behavior without claiming robustness to real sensor noise or adverse weather.

C. Deep-Learning Models for Real-Time Object Recognition

Sharanya et al. examine deep-learning-based object recognition for autonomous-vehicle safety and navigation. The paper discusses convolutional neural networks and detection architectures such as YOLO, SSD, Faster R-CNN, and Mask R-CNN, together with transformer-based vision methods and three-dimensional point-cloud processing. It highlights the importance of timely detection of vehicles, pedestrians, road signs, and barriers, while also identifying computational cost, environmental robustness, and sensor integration as challenges. This study is relevant to the perception stage of an autonomous navigation pipeline. SteadyPath currently receives object locations directly from the simulator; integrating a trained object detector is therefore a future extension rather than a completed project component.

D. A Scalable Multi-Layered DRL Approach for Decision and Control

Wu et al. present a layered deep reinforcement-learning architecture comprising sensory-data aggregation, trajectory prediction, trajectory decision, and dynamic tracking control. The Actor–Critic approach evaluates candidate trajectories and produces control commands, with validation through simulation and real-vehicle experiments. The paper provides an example of separating the navigation task into cooperating functional layers. SteadyPath similarly separates perception, state estimation, decision-making, planning, and control, but uses A* for route generation and terminal-constrained MPC for tracking rather than learning a driving policy through Actor–Critic reinforcement learning. This makes the current framework more directly structured around an explicit route and predictive constrained controller.

E. Deep Learning for Dynamic Decision-Making in Autonomous Vehicles

Nayak and Raghatate describe a framework combining YOLOv5 object detection, recurrent neural networks with attention for behavior prediction, PPO-based reinforcement learning, A* or related conventional path-planning methods, and motion control. The paper reports detection accuracy of 96.4% and trajectory-prediction accuracy of 91.8% in its stated evaluation. It illustrates how perception, prediction, planning, and control can be integrated for dynamic driving contexts. The reported metrics belong to that paper and are not SteadyPath results. SteadyPath shares the layered structure and use of A* as a planning method, but its current contribution is the simulation evaluation of terminal-constrained MPC against a baseline, not a deep-learning perception or prediction model.

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III. COMPARATIVE ANALYSIS AND RESEARCH GAP

Table I compares the five supplied studies with SteadyPath. The comparison distinguishes each paper's principal technical emphasis from the components implemented in the present project. It avoids treating the different evaluation platforms and reported metrics as directly interchangeable.

Study	Main focus and methods	Validation described in source	Relevance to SteadyPath	Difference / limitation relative to this project
Yang Zhang, Guang Xia, Jianwei Lu, and Amir Khajepour (2026)	Industrial-vehicle obstacle avoidance; safety/braking distance; terminal constraints; MPC and STSMC	Hardware-in-the-loop evaluation	Closest work: stability-aware obstacle avoidance and terminal-constrained control	SteadyPath implements a simulation-oriented integrated pipeline; it does not claim the same multidimensional stability formulation or HIL testing.
Feng-Jie Li, Chun-Yang Zhang, and C. L. Philip Chen (2026)	Image–LiDAR fusion, attention, fuzzy uncertainty representation, coordinated decision-making	Experiments and ablation studies, including extreme-weather robustness	Motivates robust perception and uncertainty-aware decisions	SteadyPath currently uses simulator ground truth, not multimodal sensor fusion or fuzzy uncertainty modeling.
C. Sharanya, K. V. Karthikeya, Mariya Princy Antony Saviour, P. S. Gomathi, V. Samuthira Pandi, and S. B. Prakalya (2024)	Deep-learning object recognition using CNN/detection and vision architectures	Analysis of recognition approaches and system challenges	Informs the virtual-perception stage and future detector integration	No trained visual detector is part of the current SteadyPath simulation results.
Liangguang Wu, Kailong Zhou, Ting Fei, Maojia Yao, Hao Han, and Honglin Li (2024)	Layered DRL, Actor–Critic trajectory evaluation, prediction and dynamic control	Simulation and real-vehicle trials described	Supports modular separation of perception, trajectory reasoning and control	SteadyPath uses A* plus terminal-constrained MPC rather than an Actor–Critic policy.
Ashu Nayak and Kapesh Subhash Raghatate (2025)	YOLOv5, RNN-attention prediction, PPO, A* and motion control	Reports 96.4% detection and 91.8% trajectory-prediction accuracy	Shows an integrated perception–prediction–planning–control design	SteadyPath focuses on controller tracking/stability metrics and baseline comparison; the paper's accuracy figures are not transferable to this project.
SteadyPath (this work)	Virtual perception, state estimation, obstacle decisions, A* route planning and terminal-constrained MPC	Software simulation; four scenario cases and quantitative baseline benchmark	Integrates route planning with predictive constrained tracking for industrial maneuvering	Current scope is limited by simulator-ground-truth perception and the need for more repeated dynamic-obstacle tests.

A. Research Gap

The reviewed studies establish strong methods for individual parts of autonomous navigation. The industrial-vehicle study [1] provides the closest stability- and terminal-constraint-oriented foundation, while [2]–[5] emphasize robust

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multimodal perception, object recognition, learned decision-making, and layered control. A practical implementation gap remains between a route planner that identifies a path and a controller that tracks it while accounting for the state at the prediction horizon. SteadyPath addresses this integration gap through an A*-generated route and an MPC controller with terminal constraints, evaluated in a repeatable virtual industrial environment. The project does not claim to solve all perception or uncertainty challenges identified in the literature.

B. Objectives

Develop a simulation environment representing an industrial travel layout with static and moving obstacles.

Provide virtual environmental information and vehicle-state information to downstream navigation modules.

Use obstacle-aware decision-making and A* to generate a navigable route or alternative route when a road is blocked.

Apply MPC with terminal constraints to predict vehicle motion and compute tracking/control actions.

Evaluate scenario behavior and compare the proposed controller with a baseline using mission and tracking metrics.

IV. PROPOSED SYSTEM AND METHODOLOGY

A. System Overview

SteadyPath follows a sequential but feedback-connected workflow: (1) simulation-environment setup; (2) virtual perception; (3) state estimation; (4) obstacle-aware decision-making; (5) A*-based motion planning; (6) terminal-constrained MPC; (7) simulation execution and testing; and (8) performance evaluation. At each simulation step, the vehicle state and surrounding-object information are updated. The planning and control stages use these updated values to determine the next motion command.

B. Simulation Environment Setup

A virtual industrial layout is configured with roads or travel corridors, a start and destination, and obstacle placements. The project test set includes a normal road, a static obstacle, a moving obstacle, and a fully blocked road. The virtual setting enables repeatable tests without requiring a physical vehicle, sensor suite, motor driver, or battery-powered chassis. The project requirements document lists Python/MATLAB and development tools such as VS Code or Jupyter Notebook; the reported evaluation is software-only.

C. Virtual Perception

The virtual perception module obtains object positions and distances from simulator-generated ground-truth information. It supplies the obstacle information required by the decision-making and planning stages. This design reduces uncertainty caused by physical sensor calibration in the current simulation, but it is not equivalent to camera, LiDAR, radar, or ultrasonic perception. No object-detection accuracy is claimed for this module.

D. State Estimation

The state-estimation stage maintains the vehicle's position, velocity, and orientation for use by the planner and controller. The project description identifies position coordinates (x, y), velocity, and orientation as the principal state information. These variables provide the current motion state needed to calculate tracking error and predict future movement.

E. Decision-Making

The decision-making module examines the vehicle state and virtual obstacle information. It determines whether the current route remains usable, whether speed or movement should be adjusted, and whether an alternative route is needed. For a moving object, the intended behavior is to respond to its position and movement by adjusting the vehicle's speed or path while maintaining clearance. For a fully blocked road, the intended behavior is to stop safely and request a new route if one is available.

F. A-Based Motion Planning*

A* is used to search for a route from the start state to the destination through the represented environment. The algorithm evaluates candidate nodes using the accumulated path cost and a heuristic estimate of the remaining cost. The resulting route provides a sequence of waypoints for the vehicle to follow. When a route is blocked, the planning stage can be invoked to find an alternative route, provided the map contains a feasible path. A* supplies the route; it does not by itself guarantee dynamically smooth tracking, which is handled by the controller. The heuristic-search basis of A* is established in [16], while broader algorithmic planning treatments are provided in [6].

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G. Model Predictive Control with Terminal Constraints

MPC repeatedly predicts the vehicle's future state over a finite prediction horizon and selects a sequence of control inputs that minimizes a defined objective while satisfying model and constraint conditions. Only the first control action is applied before the state is updated and the optimization is solved again. In SteadyPath, the MPC controller tracks the reference path generated by A* and includes terminal constraints intended to guide the predicted terminal state into a stable admissible set. This terminal condition is intended to discourage a solution that tracks the path over the short horizon but ends in an undesirable state. The general predictive-control formulation and stability role of terminal constraints are discussed in [7], [17], and [18].

A representative discrete-time formulation is:

H. min $\Sigma(k=0\ldots N-1)\ [\|e(k)\|^2Q + \|u(k)\|^2R] + \|x(N)-xref(N)\|^2P$

I. subject to $x(k+1)=f(x(k),u(k)),\ x(k)\in X,\ u(k)\in U,\ x(N)\in Xf$

Here, x represents the vehicle state, u represents the control input, e represents tracking error, N is the prediction horizon, Q and R weight tracking and control effort, P weights terminal tracking error, and Xf denotes the terminal admissible set. This expression describes the general constrained-MPC structure; the precise numerical weights, horizon length, and vehicle-model parameters are not specified in the supplied project material and are therefore not invented here.

J. Simulation Execution and Performance Evaluation

The controller is executed in the simulation loop and the vehicle response is recorded for the selected scenarios. The project evaluates collision avoidance, stability-related behavior, path smoothness, and computation-related performance. The quantitative benchmark supplied for this paper records mission duration, mean tracking error, peak lateral deviation, clearance buffer margin, dynamic detours/re-plans, and terminal-set convergence. The baseline is the existing baseline model shown in the project benchmark; the available material does not specify its internal controller formulation.

V. USE CASES AND TEST SCENARIOS

The principal use case is an autonomous industrial vehicle travelling through an internal facility from a defined start location to a destination. During the mission, it may encounter an unobstructed corridor, a stationary object, a moving object, or a blocked corridor. The vehicle is expected to follow the planned route when clear, maneuver around a static obstacle, respond cautiously to moving obstacles, and stop or re-plan when the route is blocked.

Scenario	Expected behavior	Recorded result	Status
Normal road	Follow the planned path and reach the destination safely.	Destination reached successfully.	PASS
Static obstacle	Detect the obstacle, avoid it, and continue toward the destination.	Obstacle avoided safely.	PASS
Moving obstacle	Detect the moving object, adjust speed/path, maintain safe distance, and continue.	Moving obstacle handled safely.	FAIL
Entire road blocked	Detect blockage, stop safely, and generate an alternative route if available.	Alternative route generated and vehicle continued safely.	PASS

The moving-obstacle row contains an internal reporting inconsistency: the result text states that the obstacle was handled safely, but the status is marked FAIL. Both entries are preserved as supplied. The status should be checked against the simulation log or repeated test before the paper is submitted as a final validated outcome.

VI. RESULTS AND BASELINE COMPARISON

The mission-performance benchmark compares the proposed controller with the baseline model. The benchmark states that proposed values are measured from the completed mission and baseline values are taken from the existing baseline

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model in the same simulation. The variance column is reproduced from the supplied benchmark. Table II presents the recorded values without changing their units or interpretation.

Performance criterion	Proposed controller	Baseline comparison	Measured variance
Mission duration	76.4 s	85.6 s	10.7% faster
Mean tracking error	2.52 m	14.61 m	82.8% lower error
Peak lateral deviation	5.25 m	18.91 m	72.2% lower deviation
Clearance buffer margin	3.60 m	1.30 m	+2.30 m clearance
Dynamic detours / re-plans	0	0	No difference
Terminal-set convergence	Invariant Set (Stable)	Lagging Boundary	Stable terminal entry

The original mission-performance benchmark image from the project material is reproduced below without recreating or altering its displayed values. Table II provides a text version for accessibility.



Fig. 1

A. Mission Duration

The proposed controller recorded a mission duration of 76.4 s, compared with 85.6 s for the baseline. The benchmark reports this as 10.7% faster. This result indicates that the proposed controller completed the evaluated mission in less time under the tested simulation conditions.

B. Mean Tracking Error

Mean tracking error decreased from 14.61 m for the baseline to 2.52 m for the proposed controller. The reported reduction is 82.8%. This is the largest percentage improvement among the directly numerical tracking measures in the benchmark and indicates closer adherence to the reference path in the evaluated mission.

C. Peak Lateral Deviation

Peak lateral deviation decreased from 18.91 m to 5.25 m, corresponding to the reported 72.2% reduction. Lower peak lateral deviation is consistent with better lateral path tracking during the benchmark mission. It should not be interpreted as a universal stability guarantee outside the tested setup.

D. Clearance Buffer Margin

The proposed controller recorded a clearance buffer margin of 3.60 m, compared with 1.30 m for the baseline, giving a measured increase of 2.30 m. This suggests that the proposed controller maintained a larger recorded separation margin in the benchmark.

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E. Dynamic Detours and Terminal-Set Convergence

Both controllers recorded zero dynamic detours or re-plans, so this metric shows no difference in the reported run. For terminal-set convergence, the proposed controller is recorded as "Invariant Set (Stable)," while the baseline is recorded as "Lagging Boundary." The benchmark summarizes the proposed result as stable terminal entry. These qualitative labels are reproduced as recorded; additional logs and formal definitions would be needed to independently verify the invariant-set claim.

F. Overall Interpretation

Across the reported mission benchmark, the proposed controller performs better than the baseline in mission duration, mean tracking error, peak lateral deviation, clearance buffer margin, and terminal-set convergence. There is no reported difference in the number of dynamic detours or re-plans. These results support the effectiveness of the proposed controller for the evaluated simulation mission, but the available evidence does not establish statistical significance, performance across multiple random seeds, or generalization to physical industrial vehicles. Repeated trials and detailed controller configuration data would strengthen the evaluation.

VII. DISCUSSION

The results suggest that combining A*-based route generation with terminal-constrained MPC can improve the tracking behavior of the simulated autonomous industrial vehicle compared with the baseline used in the benchmark. The lower mean tracking error and peak lateral deviation indicate that the proposed controller followed the reference route more closely in the measured run. The larger clearance margin is also consistent with more conservative obstacle separation in that run, while the shorter mission duration indicates that the improved tracking did not come at the cost of a longer measured mission. This interpretation is consistent with research on MPC-based path planning, safe tracking envelopes, hierarchical obstacle-avoidance control, and terminally constrained navigation [8]–[15].

The literature comparison clarifies the scope of the contribution. Unlike [2], [3], and [5], SteadyPath does not implement learned visual perception or multimodal sensor fusion. Unlike [4], it does not use Actor–Critic reinforcement learning as the main decision/control mechanism. Its closest conceptual relationship is to [1], particularly the use of terminal constraints and stability-aware obstacle avoidance for industrial vehicles. The distinction is the current project's software-simulation implementation and its explicit baseline measurements for mission duration, tracking error, lateral deviation, clearance margin, and terminal behavior.

The moving-obstacle status inconsistency is important because dynamic obstacles are a central motivation for the framework. It should not be hidden by rewriting the row as a pass. The result and status need to be checked against the underlying run. Similarly, zero dynamic detours/re-plans for both controllers means that the benchmark does not demonstrate a comparative advantage on that particular metric.

VIII. LIMITATIONS AND FUTURE WORK

Replace simulator-ground-truth perception with real or simulated camera, LiDAR, ultrasonic, or IMU sensing, including measurement noise and sensor failure cases.

Add explicit prediction of moving-obstacle trajectories and test multiple relative speeds, crossing paths, and close-proximity encounters.

Repeat each scenario across multiple initial conditions and report mean, standard deviation, and worst-case performance.

Document the baseline controller, vehicle model, MPC prediction horizon, sampling time, weights, constraints, and terminal-set construction to support reproducibility.

Resolve the moving-obstacle PASS/FAIL inconsistency using the simulation log and repeat the test if necessary.

Evaluate computation time and solver behavior under more complex maps and obstacle densities.

Progress toward hardware-in-the-loop testing and, later, controlled physical trials only after simulation safety and repeatability have been established.

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IX. CONCLUSION

This paper presented SteadyPath, a simulation-based framework for stability-aware autonomous industrial maneuvering. The system combines virtual perception, state estimation, obstacle-aware decision-making, A*-based path planning, and MPC with terminal constraints. Four scenario tests were documented, with successful recorded outcomes for normal-road, static-obstacle, and fully blocked-road cases. The moving-obstacle test remains unresolved because its result description and status disagree.

In the quantitative baseline benchmark, the proposed controller recorded a 76.4 s mission duration versus 85.6 s, a mean tracking error of 2.52 m versus 14.61 m, a peak lateral deviation of 5.25 m versus 18.91 m, and a clearance buffer margin of 3.60 m versus 1.30 m. It was also recorded as reaching an invariant stable terminal set, while the baseline was recorded as having a lagging boundary. Both controllers recorded zero dynamic detours or re-plans. These findings indicate improved performance on the supplied simulation benchmark. Further repeated testing, clarification of the moving-obstacle outcome, full controller-parameter reporting, and sensor-based validation are required before broader claims can be made.

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Data Availability: The scenario outcomes and quantitative benchmark values reported in this manuscript are the results recorded for the project simulation. No separate public dataset is associated with this work.

Authors' Contribution: Diwakar M contributed to conceptualization, methodology, system integration, analysis of simulation results, and manuscript preparation. Shashank D N contributed to the literature review, technical analysis, and interpretation of the planning and control methods. Rudra Prathap Singh contributed to system architecture, simulation environment planning, and integration of the navigation workflow. Snehal B contributed to test-case design, evaluation methodology, result organization, and reference preparation. B. C. Hemapriya provided supervision, technical guidance, critical review, and manuscript revision. All authors reviewed and approved the final manuscript.

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