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Safety-Oriented Model Predictive Control for Autonomous Vehicles: A Systematic Review

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Abstract

Ensuring safety in autonomous vehicles (AVs) requires predictive control methods that can handle dynamic constraints, uncertain interactions, and real-time decision making. This review examines safety-oriented model predictive control (MPC) for AVs using a PRISMA-guided screening process. From 363 records published between January 2015 and March 2026, 101 peer-reviewed studies were selected for qualitative synthesis. The literature is organized into three domains: collision avoidance and risk mitigation, trajectory tracking and path following, and intersection and coordination tasks. Across these domains, MPC has evolved from nominal tracking and geometric avoidance toward risk-aware, robust, hierarchical, and learning-enhanced formulations. Unlike broader reviews on autonomous driving control, this review focuses specifically on safety-oriented MPC and compares the reviewed literature in terms of safety mechanisms, uncertainty treatment, validation practice, computational feasibility, and deployment limitations. The review shows that MPC remains one of the most versatile frameworks for AV safety, but the evidence base is weakened by heavy reliance on simulation, inconsistent safety metrics, limited validation under uncertainty, and uneven treatment of computational feasibility. The most promising directions are hybrid architectures that combine model-based safety guarantees with uncertainty-aware prediction, learning-assisted adaptation, and scalable coordination mechanisms.

Keywords: predictive safety control; collision avoidance; trajectory tracking; cooperative driving; uncertainty-aware control; autonomous navigation

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1. Introduction

Autonomous vehicles (AVs) promise improvements in mobility, efficiency, and safety, but these benefits depend on the ability of the control stack to prevent unsafe motion under uncertainty [1–4]. Safety in AVs is not limited to lane keeping or path following; it also requires timely reaction to dynamic obstacles, uncertain surrounding agent behavior, limited sensing, actuator constraints, and rapidly changing traffic contexts [5–11]. Model predictive control (MPC) remains one of the most influential control paradigms for this problem because it optimizes future actions over a receding horizon while explicitly accounting for system dynamics and operational constraints [12–16]. This predictive and constraint-aware structure makes MPC attractive for safety-critical tasks such as collision avoidance, trajectory tracking, lane changing, overtaking, merging, and cooperative maneuvering [4,10,11,17–20].

The recent AV literature has expanded well beyond classical linear or nonlinear MPC. Current studies increasingly combine MPC with probabilistic risk models, learning-based residual estimators, perception modules, communication layers, and interaction-aware decision models [5,10,11,17,21–24]. As a result, the field now contains a wide range of formulations that differ not only in controller design but also in how they define, approximate, and validate safety. This methodological diversity has created a fragmented evidence base: some studies emphasize nominal path tracking, others focus on obstacle avoidance or risk-aware planning, while a smaller group addresses cooperative and multi-agent safety under communication and interaction constraints. Existing surveys on autonomous driving and predictive control provide a useful background, but they do not sufficiently isolate safety-oriented MPC as a review object. A focused synthesis is needed to distinguish nominal tracking results from genuine safety contributions; to compare how different studies represent risk and constraints; and to identify where the evidence remains weak, overly simulation-driven, or insufficiently connected to real-time deployment.

Although the broader autonomous driving literature includes surveys on motion planning, control, collision avoidance, and intelligent transportation systems, safety-oriented MPC has often been treated as one component within wider AV control taxonomies rather than as the central object of analysis. This distinction is important because not every MPC-based AV study provides a direct safety contribution: some studies mainly improve nominal tracking accuracy, while others explicitly encode collision avoidance, risk metrics, uncertainty propagation, robust constraints, safety filters, or cooperative conflict resolution.

The novelty of this review is therefore threefold. First, it isolates safety-oriented MPC as the primary review object and separates nominal path following contributions from studies in which safety constraints, risk mitigation, or safe interaction are central to the controller design. Second, it organizes the selected studies according to safety function—collision avoidance and risk mitigation, trajectory tracking and path following under safety constraints and intersection and coordination tasks—rather than only by controller type. Third, it evaluates the evidence base through implementation-relevant dimensions, including safety mechanism, uncertainty treatment, validation level, computational feasibility, scalability, and deployment limitations. This positioning allows the review to move beyond a descriptive collection of studies toward a critical synthesis of how MPC contributes to AV safety and where the evidence remains insufficient for real-world deployment.

To clarify the system-level position of safety-oriented MPC in autonomous driving, Figure 1 illustrates how the MPC layer interacts with perception, prediction, planning, and vehicle actuation. The figure shows that MPC does not operate as an isolated controller; rather, it receives state estimates, reference trajectories, road and lane constraints, predicted surrounding agent information, actuator limits, and safety constraints before generating steering, braking, acceleration, and safe predicted trajectory outputs.

This paper therefore presents a systematic review of safety-oriented MPC strategies for AVs using a PRISMA-guided selection process. The review covers peer-reviewed studies published between January 2015 and March 2026 and synthesizes 101 included papers across three thematic domains: collision avoidance and risk mitigation, trajectory tracking and path following, and intersection and coordination tasks. The review has four objectives: (i) to classify the main safety-oriented MPC formulations used in AV research; (ii) to compare their assumptions, safety mechanisms, uncertainty treatments, validation settings, and implementation evidence; (iii) to identify recurrent technical limitations, especially those related to computation, uncertainty, scalability, and fragmented system integration; and (iv) to highlight the most credible future research directions for deployable AV safety control. The remainder of the paper is organized as follows. Section 2 describes the review

methodology and screening logic. Section 3 presents the thematic synthesis. Section 4 discusses cross-cutting challenges and engineering deployment considerations. Section 5 outlines future research directions. Section 6 concludes the paper.

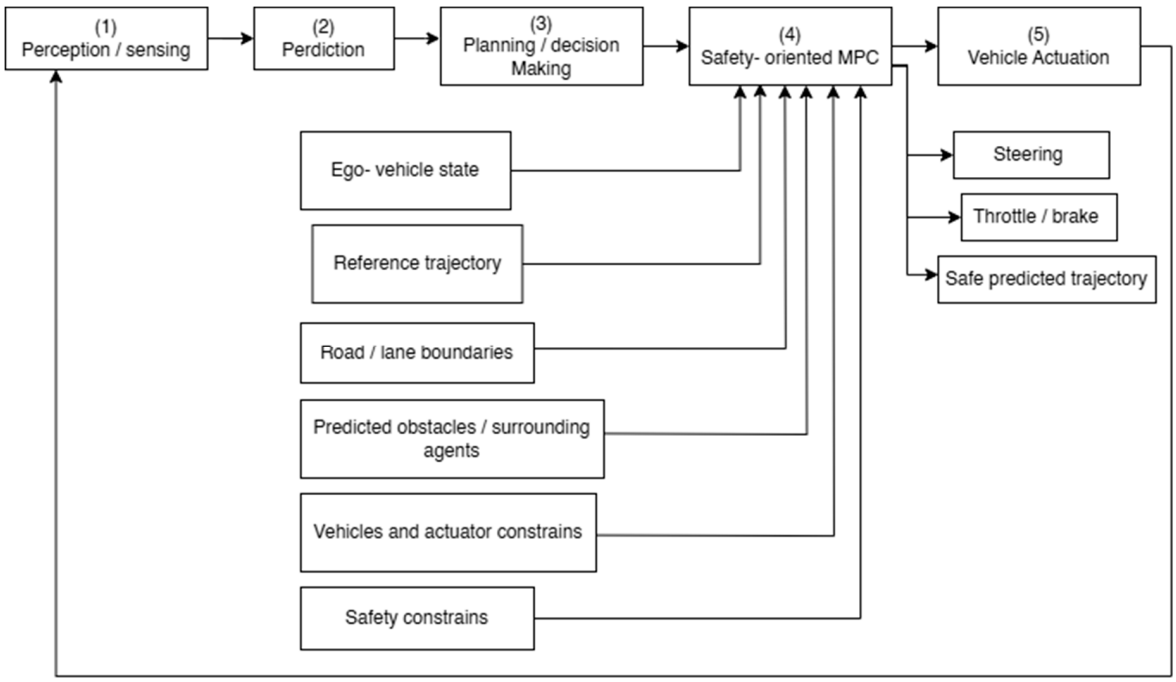


Figure 1. Position of safety-oriented MPC within the autonomous driving stack.

2. Methodology

This systematic literature review was structured according to the logic of PRISMA 2020 to improve transparency, selection traceability, and synthesis discipline. The review process followed the standard stages of identification, duplicate removal, title/abstract screening, full-text eligibility assessment, and final inclusion. Across the four selected databases, 363 records were identified; 15 duplicates were removed; 348 records were screened; 204 were excluded after title and abstract review; 144 full-text papers were assessed; 43 were excluded at full text; and 101 studies were retained for qualitative synthesis. Figure 2 summarizes the study selection process. Because the included studies differed substantially in vehicle models, scenario definitions, validation settings, uncertainty treatments, and reported metrics, the review was designed as a qualitative evidence synthesis rather than a statistical meta-analysis. In addition to identifying relevant studies, the methodology was designed to support structured comparison across safety mechanisms, MPC variants, uncertainty treatments, validation levels, and implementation-related evidence. To support transparency, reproducibility, and traceability of the selection process and inclusion criteria, this systematic review was registered on the Open Science Framework (OSF) under the same title.

2.1. Database Selection and Search Strategy

Four databases were searched because together they provide broad coverage of control, robotics, intelligent transportation, and applied automation research: IEEE Xplore, MDPI, Web of Science, and ScienceDirect. The search window covered January 2015 to March 2026, which captures the period in which safety-oriented MPC for AVs expanded rapidly in both methodological variety and application scope.

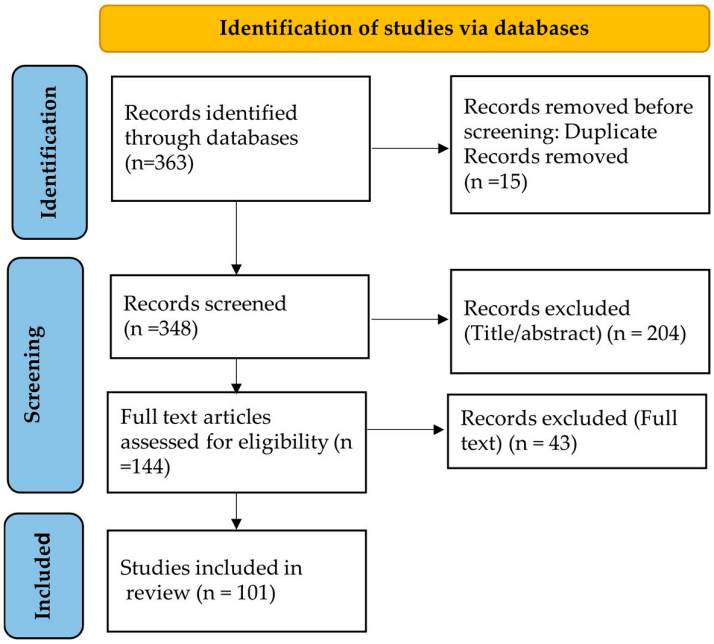


Figure 2. PRISMA 2020 flow diagram.

The search strategy combined three concept groups: (1) autonomous driving terms (e.g., autonomous vehicle, automated driving, connected autonomous vehicle), (2) predictive control terms (e.g., model predictive control, MPC, nonlinear MPC, robust MPC, stochastic MPC), and (3) safety-oriented task terms (e.g., collision avoidance, risk-aware planning, safe tracking, intersection management, lane change, overtaking, coordination). Database-specific syntax was adapted as needed, but the conceptual scope was kept constant across sources. A representative base query used to guide database adaptation is ("autonomous vehicle" OR "automated driving" OR "connected autonomous vehicle") AND ("model predictive control" OR MPC OR "nonlinear model predictive control" OR "robust MPC" OR "stochastic MPC") AND (safety OR "collision avoidance" OR "risk-aware" OR "safe tracking" OR "intersection management" OR "lane change" OR overtaking OR coordination).

To further clarify the composition of the reviewed evidence base, the 101 included studies were also grouped by publication venue or source category after the final selection stage. This classification is distinct from the database search process, since the four searched databases were used to identify candidate records, whereas the distribution below describes the publication sources of the final included studies. IEEE-affiliated journals and conference proceedings represented the largest share of the included literature, with 58 studies, corresponding to approximately 57.4% of the final corpus. MDPI journals contributed 16 studies, or approximately 15.8%, while IFAC-PapersOnLine contributed 11 studies, or approximately 10.9%. Elsevier journals and proceedings, excluding IFAC-PapersOnLine papers counted separately, contributed 10 studies, or approximately 9.9%. The remaining 6 studies, or approximately 5.9%, were published by other sources. This distribution indicates that the reviewed literature is mainly concentrated in control, intelligent transportation, vehicle systems, and automation-oriented publication venues, which is consistent with the technical focus of safety-oriented MPC for autonomous vehicles.

2.2. Screening, Eligibility, and Data Extraction

Screening was performed in staged form. After duplicate removal, titles and abstracts were checked against predefined relevance criteria. Potentially eligible papers then underwent full-text assessment. The purpose of this staged process was to exclude papers

that used MPC in autonomous driving contexts without making safety a primary control objective, while retaining studies in which safety constraints, collision mitigation, safe motion planning, or coordination under risk formed part of the core contribution.

To reduce subjective selection bias, each paper was assessed according to the same eligibility logic: the study had to include an identifiable MPC formulation, an autonomous or connected driving application, and a safety-related control objective. During full-text assessment, particular attention was given to whether safety was treated as a central design element rather than as a secondary performance outcome.

2.2.1. Inclusion Criteria

A study was retained when it satisfied all of the following conditions: it proposed or applied MPC or a clearly defined MPC variant; the application domain was autonomous or connected autonomous driving; the control problem was explicitly safety-related; the paper was peer-reviewed; and the publication fell within the selected time window.

2.2.2. Exclusion Criteria and Final Selection

Studies were excluded when safety was peripheral rather than central, when MPC was applied outside the AV domain, when the work was non-peer-reviewed, or when the full text did not support inclusion after detailed inspection. Common reasons for full-text exclusion were weak thematic fit, absence of a genuine safety objective, or use of predictive control in contexts unrelated to autonomous driving.

For each included study, information was extracted on MPC variant, application scenario, safety mechanism, uncertainty treatment, validation setting, and stated limitations. Additional implementation-related information was also extracted when available, including reported computation time, solver type, prediction horizon, sampling time, hardware or simulation platform, and evidence of real-time feasibility. During synthesis, the studies were compared along dimensions that matter directly for scientific credibility: controller structure, safety representation, interaction modeling, reported real-time feasibility, and level of validation, including simulation, software-in-the-loop, hardware-in-the-loop, or experimental testing. These extracted fields were then used to support the thematic classification and the cross-domain critical comparison presented later in the review.

2.3. Thematic Classification and Comparative Synthesis

To synthesize the literature in a structured manner, the included studies were classified into one or more of three domains according to the primary safety function addressed by MPC: collision avoidance and risk mitigation; trajectory tracking and path following under safety constraints; and intersection/coordination tasks involving multi-agent or interactive traffic scenarios. Table 1 summarizes the thematic coverage of the included studies across these three safety-oriented MPC application domains.

Table 1. Thematic coverage of included studies across safety-oriented MPC application domains.

Reference	Collision Avoidance	Trajectory Tracking	Coordination
[5,6,12–14,25–41]	✓		
[1,2,7,8,15–18,42–62]		✓	
[3,4,63–65]			✓
[9,21,66–81]	✓	✓	
[10,11,22,23,82–92]	✓		✓
[93–95]		✓	✓
[19,20,24,96–101]	✓	✓	✓

This thematic organization was used for comparison rather than as a claim that the three categories are fully disjointed. Several papers span multiple functions, especially those combining tracking with obstacle avoidance or coordination with risk-aware planning. In such cases, studies were discussed in the domain most closely aligned with their principal safety contribution. The classification was also used to support cross-domain comparison of MPC variants, safety mechanisms, uncertainty treatment, validation practice, computational feasibility, and implementation limitations. This comparative structure was adopted to avoid presenting the literature only as a descriptive list of studies and to highlight recurring trade-offs between safety guarantees, real-time feasibility, scalability, and deployment readiness.

3. Thematic Synthesis of the Literature

This section synthesizes the included studies by emphasizing cross-study patterns rather than sequential descriptions of individual papers. The focus is on how each class of MPC formulation contributes to safety, how safety is represented, what assumptions are imposed, and how convincingly the claims are validated. The equations and algorithmic patterns are retained only as compact representative abstractions; they are used to support comparison across MPC variants rather than to provide a tutorial derivation of each method.

To keep the synthesis comparative, the reviewed formulations are grouped by their dominant safety mechanism: nominal and constraint-based MPC, robust and stochastic MPC, learning-enhanced MPC, and cooperative or hierarchical MPC. Nominal and constraint-based MPC mainly provide reference tracking and explicit road, obstacle, and actuator constraints; robust and stochastic MPC address bounded or probabilistic uncertainty; learning-enhanced MPC improves prediction or model adaptation; and cooperative or hierarchical MPC extends safety reasoning to interacting agents and layered decision making. This grouping is used to interpret the studies by safety role rather than by isolated mathematical form.

Figure 3 presents a generic safety-oriented MPC architecture that summarizes the recurring components found across the reviewed studies, including input information, prediction, cost design, safety constraints, uncertainty handling, optimization, and fallback safety mechanisms.

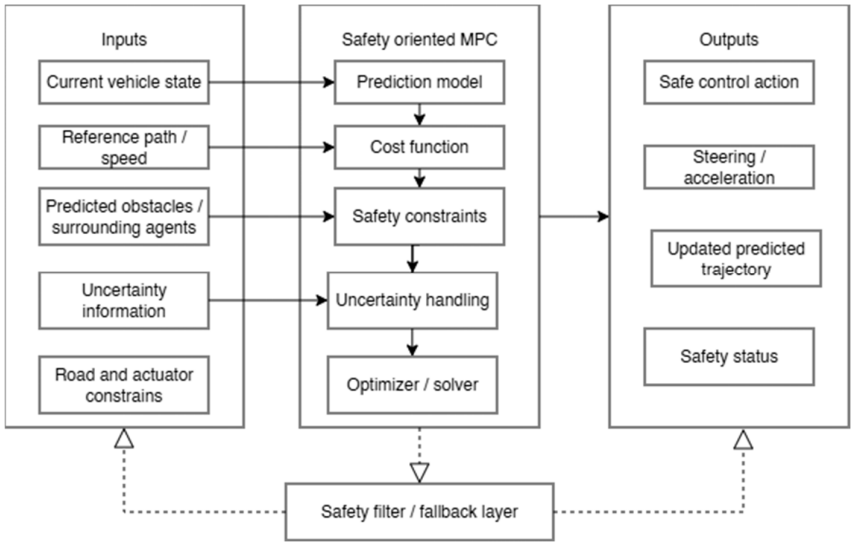


Figure 3. Generic architecture of safety-oriented MPC for autonomous vehicles.

Figure 4 maps the main MPC variants to their dominant safety mechanisms and provides a taxonomy for interpreting the formulations reviewed in the following subsections.

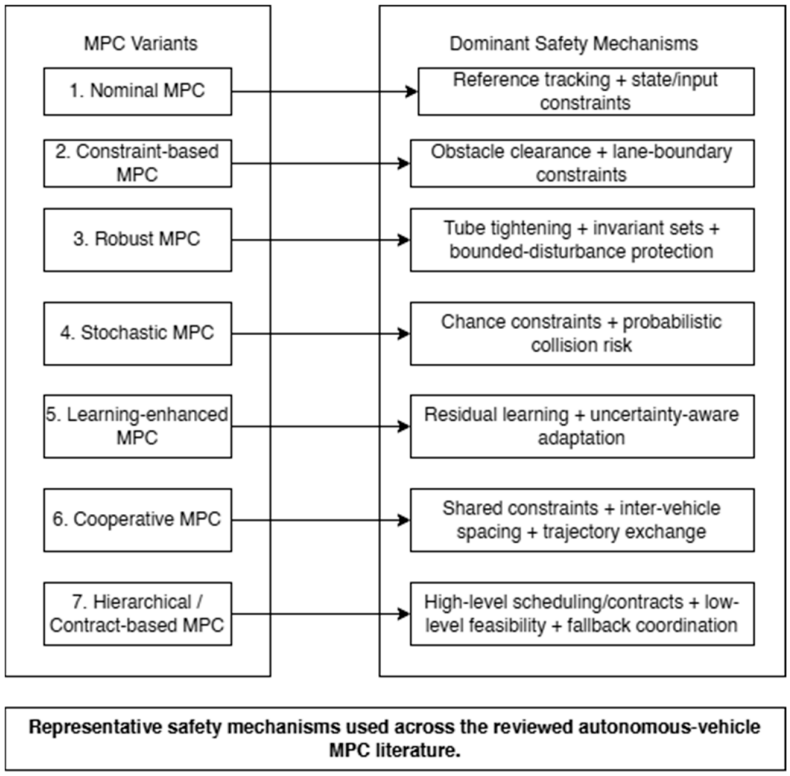


Figure 4. Taxonomy of safety-oriented MPC variants and dominant safety mechanisms.

3.1. Collision Avoidance and Risk Mitigation

Collision avoidance is one of the most fundamental safety requirements in autonomous driving. MPC is widely used for this purpose because it predicts future vehicle states while enforcing obstacle, stability, and actuation constraints within a unified optimization framework. In the reviewed literature, collision-avoidance MPC can be grouped into three main directions: constraint-based and reactive methods, uncertainty-aware and risk-aware control, and perception-aware or learning-augmented safety architectures. Across these groups, the main cross-study trend is a shift from simple geometric obstacle avoidance toward probabilistic, interaction-aware, and dynamically feasible safety planning. Therefore, the following synthesis evaluates collision-avoidance MPC not only by whether it produces collision-free trajectories but also by how it encodes safety, handles uncertainty, preserves real-time feasibility, and supports deployment in dynamic traffic environments.

To provide a common analytical frame, Equations (1)–(4) summarize the recurring structure of collision-avoidance MPC: vehicle prediction, reference tracking, obstacle-related safety terms, state/input constraints, and receding-horizon re-optimization. They are included as a compact comparative template rather than as a tutorial derivation or a single formulation shared by all reviewed studies. In practice, the optimization is re-solved at each control update using refreshed state estimates and obstacle predictions.

$$x(k+1) = f(x(k), u(k)) \tag{1}$$

$$x(k) = [X(k)\ Y(k)\ \psi(k)\ v(k)]^T,\ u(k) = [a(k)\ \delta(k)]^T \tag{2}$$

$$\min_{u(0),\ldots,u(N-1)} J = \sum_{k=0}^{N-1} \left(\left(x(k) - x_{ref}(k) \right)^T Q \left(x(k) - x_{ref}(k) \right) + u(k)^T R u(k) + \sum_{j=1}^{n_{obs}} w_j \Phi\left(d_j(k) \right) \right) + \left(x(N) - x_{ref}(N) \right) \tag{3}$$

$$x(k) \in X,\ u(k) \in U,\ k = 0, \ldots,\ N-1 \tag{4}$$

where $x(k)$ is the system state vector at step k, while $u(k)$ is the control input vector; $X(k)$ and $Y(k)$ are the global position; $\psi(k)$ is the yaw/heading angle; $v(k)$ is the longitudinal speed; $a(k)$ is the longitudinal acceleration command; and $\delta(k)$ is the steering command. Here, J is the objective function over the prediction horizon N; $x_{\text{ref}}(k)$ is the reference state or trajectory at step k; Q and R are weighting matrices for tracking error and control effort, respectively, where $Q \succeq 0$ is a positive semi-definite weighting matrix; and $R \succ 0$ is a positive definite weighting matrix. The initial selection of these weighting matrices can be carried out using Bryson's rule; w_j is the weight assigned to obstacle j; $\Phi(\cdot)$ is the obstacle-related penalty function, used to increase the cost as the ego vehicle approaches an obstacle, thereby encouraging obstacle clearance in the optimized trajectory; $d_j(k)$ is the distance to obstacle j at step k; and n_{obs} is the number of obstacles considered.

Algorithm 1 summarizes this pattern, which is common across the reviewed collision-avoidance MPC implementations.

Algorithm 1: Receding-horizon execution of collision-avoidance MPC

Inputs: estimation of current state $x(0)$; reference $\left\{x_{ref}(k)\right\}_{k=0}^{N}$; predictions of obstacle $\left\{p_j^{obs}(k)\right\}_{k=0}^{N}$; horizon N.
Output: applied control $u(0)$.

1. Construct MPC problem using Equations (1)–(4) and the selected obstacle safety encoding.
2. Solve to get the optimal sequence $\left\{u_{opt}(k)\right\}_{k=0}^{N-1}$.
3. Apply only the first input $u_{opt}(0) \longrightarrow u(0)$.
4. Update both $x(0)$ and obstacle predictions; shift the horizon; repeat Steps 1–3.

3.1.1. Constraint-Based and Reactive Collision Avoidance

Constraint-based and reactive collision-avoidance MPC primarily encodes safety through geometric clearance, lane or road boundaries, and actuator-feasible evasive behavior. Across the reviewed studies, APF/sigmoid barriers, hard safety constraints, NMPC escape maneuvers, and integrated steering–braking or yaw control strategies serve the same core purpose: keeping the predicted trajectory outside unsafe regions while preserving vehicle feasibility [11–14,20,25,26,28,58,67,68,79,86,96–98]. The main strength of this group is implementation simplicity and clear geometric interpretability; the main limitation is that clearance-based safety remains sensitive to perception error, obstacle intent uncertainty, and rapidly changing maneuver space.

More structured path-generation mechanisms, including time-scaled collision-cone MPC, CQP-based MPC, safety-tunnel MPC, and hybrid MPC–spline lane-change control, improve path smoothness and reduce local-minimum effects [69,70,83,93]. Therefore, the cross-study trend is a shift from reactive obstacle repulsion toward corridor- or maneuver-structured collision avoidance, where timing, road curvature, and dynamic feasibility become as important as obstacle distance.

Equations (5)–(11) group the main distance-based safety encodings used in constraint-based collision-avoidance MPC, including geometric clearance, hard and soft distance constraints, slack penalties, repulsive potentials, sigmoid shaping, and speed-dependent safety margins.

$$p(k) = \begin{bmatrix} X(k) \\ Y(k) \end{bmatrix}, d_j(k) = \| \ p(k) - p_j^{\text{obs}}(k) \ \|_2 \tag{5}$$

where $p_j^{\text{obs}}(k)$ is the predicted position of obstacle j at step k.

To guarantee collision avoidance, a hard safety constraint is imposed by requiring the distance between the ego vehicle and each obstacle to remain above a prescribed minimum clearance, expressed as:

$$d_j(k) \geq d_{\min}(k) \tag{6}$$

where $d_{\min}(k)$ represents the required minimum safety distance, which may be constant or time-varying.

To improve feasibility in constrained or highly dynamic scenarios, the hard clearance constraint can be relaxed by introducing a non-negative slack variable $\epsilon_j(k)$. This results in the following soft-constraint formulation:

$$d_j(k) \geq d_{\min}(k) - \epsilon_j(k), \epsilon_j(k) \geq 0 \tag{7}$$

where larger values of $\epsilon_j(k)$ correspond to greater violations of the clearance requirement and are used to maintain feasibility when strict satisfaction of the hard constraint is not possible.

Violations of the soft distance constraint are penalized in the objective function through an additional slack penalty term defined as:

$$J_{\text{slack}} = \rho \sum_{k=0}^{N-1} \sum_{j=1}^{n_{\text{obs}}} \epsilon_j^2(k) \tag{8}$$

where ρ is a tuning coefficient that regulates the severity of constraint violation penalties, and n_{obs} denotes the number of obstacles considered.

In reactive collision-avoidance formulations, the hard or soft clearance constraints are often complemented by smooth repulsive potentials to encourage early avoidance behavior. A commonly used artificial potential field penalty is defined as:

$$\Phi_{\text{APF}}(d) = \begin{cases} 0, & d \geq d_0 \\ \eta\left(\frac{1}{d} - \frac{1}{d_0}\right)^2, & d < d_0 \end{cases} \tag{9}$$

where η controls the repulsion strength, d denotes the obstacle distance, and d_0 is the influence distance beyond which the repulsive effect is disabled.

To ensure smooth safety shaping near the minimum clearance boundary, a sigmoid-based mapping can be employed, which is given by:

$$\sigma(d_j(k)) = \frac{1}{1 + \exp\left(-\alpha\left(d_j(k) - d_{\min}(k)\right)\right)} \tag{10}$$

where α determines the steepness of the transition, and $d_{\min}(k)$ denotes the minimum clearance threshold.

In medium- and high-speed driving scenarios, the minimum clearance is often modeled as a time-varying quantity to reflect speed-dependent risk, leading to:

$$d_{\min}(k) = d_0 + \tau \mid v_{\text{rel}}(k) \mid \tag{11}$$

where d_0 is the base clearance, τ is a time-headway parameter, and $v_{\text{rel}}(k)$ denotes the relative speed magnitude at step k.

Algorithm 2 summarizes how these distance constraints and shaping terms are assembled within the receding-horizon loop for constraint-based and reactive collision avoidance.

Algorithm 2: Constraint-based/reactive MPC assembly for obstacle avoidance

Inputs: $x(0)$, $\left\{x_{ref}(k)\right\}$, $\left\{p_j^{obs}(k)\right\}$, design parameters $(d_0, \tau, \rho, \eta, \alpha)$.
Output: applied control $u(0)$.

1. Compute clearance distances $d_j(k)$ using Equation (5) over the horizon (based on predicted obstacle positions).
2. Select the safety encoding: enforce hard clearance via Equation (6) or soft clearance via Equations (7) and (8).
3. If using reactive shaping, augment the objective with Φ_{APF} in Equation (9) and/or a sigmoid-based safety shaping term via Equation (10).
4. When speed-dependent safety is necessary, update $d_{min}(k)$ using Equation (11).
5. Solve the MPC optimization and apply $u(0) = u_{opt}(0)$; repeat at the next control update.

3.1.2. Risk-Aware and Robust Control Under Uncertainty

Risk-aware and robust MPC extends collision avoidance from deterministic clearance to safety under uncertain obstacle behavior, perception, control inputs, and vehicle dynamics. Across the reviewed studies, Monte Carlo risk estimation, chance constraints, robust/tube-based formulations, reachability analysis, and adaptive updates serve a common purpose: preserving feasible safety margins when future motion or model behavior is uncertain [6,9–11,27,59,85,94]. Compared with purely geometric methods, these approaches provide stronger uncertainty-aware safety interpretations, but their credibility depends on the realism of the assumed probability models, disturbance bounds, or reachable sets.

A cross-study trend is the use of risk-shaped decision making rather than distance-only avoidance. Collision probability, time-to-collision, overtaking risk, and uncertainty-calibrated margins allow controllers to distinguish situations with similar geometry but different hazard levels [85,94]. This is particularly relevant in overtaking and emergency lane-change scenarios, where the controller must decide not only how to maneuver but also whether the maneuver should be attempted.

The practical limitation is computational and modeling burden. Robust and stochastic safety mechanisms can improve confidence under uncertainty, but they may become conservative or difficult to solve online, especially in high-speed, mixed-traffic, or rapidly changing scenarios. Therefore, their deployment value depends on whether uncertainty assumptions are valid and whether optimization remains feasible within real-time driving constraints.

Equations (12)–(15) summarize the two main uncertainty-handling patterns in the reviewed collision-avoidance literature: probabilistic safety through chance constraints and Monte Carlo risk estimation and robust safety through bounded disturbances and invariant safe sets.

$$\Pr\left(d_j(k) \geq d_{\min}\right) \geq 1 - \epsilon \tag{12}$$

where $Pr(\cdot)$ denotes probability, $d_j(k)$ is the uncertain distance to obstacle j at step k, $d_{\min}$ is the required clearance, and ϵ represents the allowable risk level.

In practice, this probabilistic constraint is commonly approximated using Monte Carlo sampling of obstacle predictions. The resulting empirical collision probability estimate is computed as:

$$\hat{p}_{\text{coll}}(j,k) = \frac{1}{N_s}\sum_{s=1}^{N_s} \| \left(d_j^{(s)}(k) < d_{\min}\right) \leq \epsilon \tag{13}$$

where $\hat{p}_{\text{coll}}(j,k)$ is the estimated probability of violating the clearance constraint for obstacle j at step k, N_s is the number of Monte Carlo samples, and the indicator function counts the proportion of samples for which the clearance condition is violated.

Robust MPC formulations instead model uncertainty as an additive bounded disturbance acting on the system dynamics, leading to:

$$x(k+1) = f(x(k), u(k)) + w(k), w(k) \in W \tag{14}$$

where $w(k)$ represents an unknown disturbance and W denotes a bounded uncertainty set.

To guarantee safety under all admissible disturbances, reachability-based and invariant set approaches enforce that the predicted state remains within a predefined safe set throughout the horizon, expressed as:

$$x(k) \in S_{\text{safe}}, k = 0, \ldots, N \tag{15}$$

where S_{safe} denotes the set of states that satisfy safety requirements such as collision avoidance and vehicle stability.

Algorithm 3 summarizes the sampling-based risk evaluation step used to convert uncertain obstacle predictions into collision risk constraints for the MPC solver.

Algorithm 3: Monte Carlo risk evaluation for chance-constrained MPC

Inputs: predicted obstacle distribution/model; horizon N; number of samples N_s; clearance threshold d_{min}; risk bound ε.
Output: estimated collision risk constraint values $\hat{P}_{coll}(j,k)$.

1. For each obstacle j and time k, draw N_s samples of predicted obstacle motion.
2. For each sample s, compute clearance $d_j^{(s)}(k)$ using the distance definition in Equation (5).
3. Estimate collision probability $\hat{P}_{coll}(j,k)$ using Equation (13).
4. Pass the constraint $\hat{P}_{coll}(j,k) \leq \varepsilon$ to the MPC solver (Algorithm 1, Step 1) and re-solve.

3.1.3. Perception-Aware and Learning-Augmented Safety Architectures

Perception-aware and learning-augmented MPC architectures extend collision avoidance by connecting the controller with prediction, learning, communication, or supervisory safety layers. Across the reviewed studies, pedestrian forecasting, game-theoretic interaction modeling, Gaussian Process residual learning, dual-layer safety control, and event-triggered coordination all serve the same broader purpose: improving anticipation while retaining explicit safety constraints or fallback mechanisms [5,10,24,42,82].

The main cross-study trend is that collision avoidance is increasingly treated as an interaction-aware safety problem rather than a single-vehicle obstacle bypass task. In mixed traffic, surrounding vehicles and pedestrians are active agents whose future motion can affect whether an evasive maneuver remains feasible. Therefore, cooperative crash-avoidance, lane-change decision models, graph-search-assisted planners, and Stackelberg-game formulations improve safety mainly by representing maneuver dependency, relative intent, and conflict resolution [17,19,84,86,98,99].

The main limitation is safety assurance. Learning and perception modules can improve model accuracy and anticipation, but they can also introduce prediction error, distribution shift, and communication delay into the MPC constraints. For this reason, the strongest

architectures use learning to support prediction or adaptation while retaining explicit safety envelopes, uncertainty-aware tightening, or fallback filters inside the MPC framework.

Equations (16)–(20) group the main mechanisms used in perception-aware and learning-augmented MPC: forecast-based obstacle prediction, learned residual dynamics, uncertainty-aware constraint tightening, safety-filter correction, and event-triggered information exchange.

$$p_j^{\text{obs}}(k) = Predict_j(k) \text{ (optionally with uncertainty } \Sigma_j^{\text{obs}}(k)) \tag{16}$$

where $Predict_j(\cdot)$ denotes the prediction model associated with obstacle j, and $\Sigma_j^{\text{obs}}(k)$ represents the corresponding prediction uncertainty, for example in the form of a covariance matrix.

Learning-augmented MPC schemes often enhance the nominal prediction model by incorporating a data-driven correction term to compensate for unmodelled dynamics. A common formulation based on Gaussian Processes augments the nominal dynamics as:

$$x(k+1) = f_{\text{nom}}(x(k), u(k)) + \mu_{GP}(x(k), u(k)) \tag{17}$$

where $f_{\text{nom}}(\cdot)$ is the physics-based nominal model and $\mu_{GP}(\cdot)$ denotes the *GP* mean function capturing residual modeling errors.

To account for uncertainty in the learned model and maintain safety guarantees, the minimum clearance constraint can be tightened using the GP predictive uncertainty, leading to:

$$d_j(k) \geq d_{\min} + \beta \sigma_{GP}(x(k), u(k)) \tag{18}$$

where $\sigma_{GP}(\cdot)$ is a measure of *GP* uncertainty, β is a confidence scaling factor, and $d_{\min}$ is the baseline minimum clearance.

Dual-layer safety architectures introduce a safety filter that minimally modifies the nominal control input while enforcing safety constraints. This safety-filtered input is obtained by solving:

$$u_{\text{safe}} = \underset{u}{\text{argmin}} \parallel u - u_{\text{nom}} \parallel_2^2 \text{ s.t. } h(x,u) \geq 0,\ u \in U \tag{19}$$

where u_{nom} is the nominal control input produced by the primary MPC, $h(x,u)$ is a safety constraint function, U is the admissible input set, and $\parallel \cdot \parallel_2$ denotes the Euclidean norm.

In cooperative or decentralized settings, communication between agents is often regulated using an event-triggered mechanism to reduce bandwidth usage. A transmission event is triggered whenever the deviation signal exceeds a predefined threshold, which can be expressed as:

$$\text{Transmit} \iff \parallel e(t) \parallel > \delta \tag{20}$$

where $e(t)$ denotes the triggering error signal, such as the deviation since the last transmission, and δ is the event-triggering threshold.

Algorithm 4 summarizes how a safety-filter layer can act as a fallback mechanism when the nominal MPC prediction approaches a safety violation.

Together, Equations (5)–(20) and Algorithms 1–4 map the reviewed collision-avoidance literature into three implementable MPC patterns: distance-based constraint encoding, uncertainty-aware risk or robustness treatment, and perception/learning integration with safety backstops. Table 2a–c summarize these patterns by technique and control objective. Overall, the main trade-off is between simplicity and uncertainty handling: geometric and reactive methods are easier to implement, while robust, risk-aware, perception-enhanced, and learning-supported methods improve anticipation and resilience but increase compu-

tational burden and safety assurance requirements.

Algorithm 4: Safety-filter integration for dual-layer MPC

Inputs: nominal MPC input u_{nom}; current state x; admissible input set U; safety function $h(x, u)$.
Output: applied control u_{app}.

1. Compute u_{nom} from the primary MPC (Algorithm 1).
2. If the predicted trajectory violates (or approaches violation of) the safety condition, solve Equation (19) to obtain u_{safe}.
3. Apply $u_{app} = u_{safe}$; otherwise, apply $u_{app} = u_{nom}$.
4. In cooperative settings, update shared information only if the trigger condition in Equation (20) is satisfied, then re-run Algorithm 1.

Table 2. (**a**). Summary of constraint-based and reactive MPC techniques for collision avoidance and risk mitigation. (**b**). Summary of risk-aware and robust MPC techniques for collision avoidance and risk mitigation. (**c**). Summary of perception-enhanced and interaction-aware MPC architectures for collision avoidance and risk mitigation.

(**a**)

Technique/Method	Ref.	Control Objective
Sigmoid/APF safety barriers	[13,14,28,29]	Geometric repulsion to enforce obstacle clearance
Time-varying obstacle margins	[29]	Dynamic scaling of safety zones relative to obstacle motion
Nonlinear MPC (NMPC)	[25,66]	Execute evasive actions under realistic vehicle dynamics
Hard safety constraints	[12,26,67]	Enforce vehicle and lane boundary constraints for local steering and lane-keeping maneuvers
Emergency collision-avoidance MPC with AFS and DYC	[86]	Coordinate steering and yaw control for collision-imminent evasive maneuvers
Collision-imminent steering on curved roads	[97]	Preserve obstacle clearance and lateral stability during high-speed curved road avoidance
Integrated drifting and direct yaw-moment NMPC	[68]	Maintain active safety and maneuver feasibility near handling limits
Hybrid MPC and spline-based lane-change control	[93]	Generate smooth and feasible lane-change trajectories under obstacle constraints
Integrated steering and differential braking	[96]	Improve emergency collision avoidance through multi-actuator coordination
Time-scaled collision-cone MPC	[98]	Represent relative motion collision risk and safe passage during avoidance maneuvers
CQP-based collision-avoidance MPC	[99]	Solve constrained obstacle-avoidance planning with improved path feasibility
Safety-tunnel-based MPC with potential functions	[85]	Maintain a safe corridor for emergency navigation in constrained environments

Table 2. *Cont.*

(**a**)		
Technique/Method	**Ref.**	**Control Objective**
Lane-change collision-avoidance MPC	[69]	Balance lane-change execution, obstacle clearance, and control smoothness
Overtaking trajectory planning with obstacle avoidance	[70]	Generate collision-free overtaking maneuvers on curved roads with static and moving obstacles
(**b**)		
Technique/Method	**Ref.**	**Control Objective**
Monte Carlo risk estimation	[9]	Evaluate probability of collision across candidate paths
Reachability-based MPC	[11]	Maintain invariant safe sets under bounded uncertainty
Robust MPC (RMPC)	[6,10]	Guarantee safety under model mismatch and stochastic uncertainty
Adaptive MPC	[21,27]	Adjust control model online based on environmental or system changes
Risk-aware nonlinear MPC	[94]	Incorporate collision risk directly into the predictive optimization problem
Risk assessment and overtaking trajectory planning	[85]	Evaluate overtaking risk and generate safe maneuvers under opposing-traffic uncertainty
(**c**)		
Technique/Method	**Ref.**	**Control Objective**
Pedestrian-aware MPC (DL-based)	[5]	Forecast pedestrian intent for proactive avoidance
Game-theoretic MPC	[10]	Predict and respond to other agents' strategies in shared environments
Dual-layer MPC	[42]	Combine nominal control with independent safety override
GP-enhanced MPC	[24]	Learn residual dynamics for improved safety prediction
Event-triggered collision coordination	[82]	Manage collisions through decentralized planning under sparse communication
Cooperative crash-avoidance framework in mixed traffic	[86]	Coordinate collision-avoidance behavior in collision-imminent mixed-traffic scenarios
MPC decision-making with lane-changing time consideration	[19]	Incorporate maneuver timing and surrounding-vehicle interaction into emergency decisions
Receding-horizon control with graph search for multi-agent planning	[84]	Improve multi-agent trajectory planning for conflict-aware avoidance
Stackelberg differential lane-change game with MPC	[17]	Model strategic interaction during lane-change conflict resolution

3.2. Trajectory Tracking and Path Following

Trajectory tracking is a core AV control function because the vehicle must follow a planned path while satisfying dynamic, physical, comfort, and safety constraints. Across the reviewed studies, tracking-oriented MPC can be grouped into three main directions: nominal and adaptive tracking, robust and learning-enhanced tracking under uncertainty, and comfort- or context-aware formulations. The cross-study trend is that path following has evolved from nominal reference tracking into a broader safety-oriented motion control problem, where lateral accuracy, longitudinal regulation, obstacle accommodation, actuator feasibility, road curvature, tire adhesion limits, and real-time implementation are increasingly treated together rather than as isolated objectives [1,7,8,10,22,24,31,42–47,49,51,71,74,90]. Therefore, the following synthesis evaluates tracking MPC not only by tracking error but also by robustness, comfort, actuator feasibility, and deployment relevance.

Equations (21)–(24) summarize the common tracking MPC template used to compare the reviewed studies: tracking error definition, vehicle prediction, finite-horizon tracking cost, and state/input constraints.

$$e(k) = x(k) - x_{\text{ref}}(k) \tag{21}$$

where $x(k)$ is the current or predicted system state and $x_{\text{ref}}(k)$ is the desired reference state at the same step.

The system dynamics used for prediction over the horizon are given by:

$$x(k+1) = f(x(k), u(k)) \tag{22}$$

where $f(\cdot)$ denotes the possibly nonlinear vehicle model employed by the MPC controller.

Based on the tracking error definition, the finite-horizon tracking objective is formulated to penalize both state deviation and control effort, resulting in the cost function:

$$\min_{u(0),\ldots,u(N-1)} J = \sum_{k=0}^{N-1} \left(e(k)^T Q e(k) + u(k)^T R u(k)\right) + e(N)^T P e(N) \tag{23}$$

where J is the tracking cost over the prediction horizon N, Q and R are positive semi-definite weighting matrices that penalize tracking error and control effort, respectively, and P is the terminal weighting matrix applied to the final tracking error.

The optimization problem is subject to state and input constraints enforced at each step of the prediction horizon, expressed as:

$$x(k) \in X, u(k) \in U, k = 0, \ldots, N-1 \tag{24}$$

where X and U are the admissible sets for the state and input, respectively.

3.2.1. Nominal and Adaptive MPC for Tracking

Nominal and adaptive tracking MPC provides the baseline structure for path following under vehicle and input constraints. Across the reviewed studies, linear, nonlinear, adaptive, and hybrid MPC formulations are used to improve tracking accuracy, update model parameters, switch operating modes, or maintain performance under changing driving conditions [7,43–46,48,58]. Their main strength is practical suitability for structured road following tasks and real-time implementation; their main limitation is that safety depends strongly on whether model updates, mode switching, and constraint handling remain reliable under disturbances, perception uncertainty, and rapidly changing road conditions.

Recent studies extend this baseline in three directions: adaptive prediction horizons for curvature-dependent tracking, hierarchical or integrated planning-and-control structures, and specialized motion control designs for tire adhesion limits, drifting, steering torque actuation, and four-wheel-independent steering/driving [33–35,38–40,71,72,87,100]. The cross-study trend is that nominal and adaptive tracking MPC is no longer limited to lateral error correction; it increasingly shapes dynamically feasible and context-aware motion according to road geometry, vehicle architecture, and operating speed.

Equations (25)–(27) group the main prediction structures used in nominal, adaptive, and hybrid tracking MPC: linearized vehicle prediction, online parameter adaptation, and mode-dependent dynamics.

$$x(k+1) = A(k)x(k) + B(k)u(k) + c(k) \tag{25}$$

where $A(k)$ and $B(k)$ are the possibly time-varying system matrices obtained from linearization, $c(k)$ is an affine offset term accounting for higher-order dynamics, and $x(k)$ and $u(k)$ denote the state and control input, respectively.

To address changes in vehicle dynamics and environmental conditions, adaptive MPC formulations explicitly update model parameters online. A compact representation of such an adaptive model is given by:

$$x(k+1) = f(x(k), u(k); \theta(k)), \theta(k+1) = \theta(k) + \Delta\theta(k) \tag{26}$$

where $\theta(k)$ is the vector of estimated or adapted model parameters at step k, $\Delta\theta(k)$ denotes the parameter-update increment obtained from online identification, and $f(\cdot; \theta(k))$ represents the parameterized prediction model.

Hybrid MPC approaches further extend adaptive schemes by allowing the controller to switch between multiple candidate models or control modes. This behavior can be expressed by introducing a discrete mode variable, leading to:

$$x(k+1) = f_{m(k)}(x(k), u(k)), m(k) \in \mathcal{M} \tag{27}$$

where $m(k)$ denotes the active mode at step k, $\mathcal{M}$ is the finite set of admissible modes, and $f_{m(k)}(\cdot)$ is the dynamics model associated with the selected mode.

Algorithms 5 and 6 summarize how these prediction structures are used in nominal, adaptive, and hybrid tracking MPC loops.

Algorithm 5: Nominal tracking MPC (linear/linearized MPC execution)

1. At time k, get $x(k)$ and the reference sequence $\{x_{\text{ref}}(k), x_{\text{ref}}(k+1), \ldots, x_{\text{ref}}(k+N)\}$.
2. Build the prediction model using Equation (25) (or update linearization terms $A(k), B(k), c(k)$).
3. Solve Equations (23) and (24) over the horizon to obtain $\left\{u_{opt}(i)\right\}_{i=0}^{N-1}$.
4. Apply the first input $u_{opt}(0) \longrightarrow u(k)$, then shift the horizon and repeat.

Algorithm 6: Adaptive/hybrid tracking MPC (parameter/mode update + MPC solve)

1. Estimate/refresh the parameter vector $\theta(k)$ (or select mode $m(k)$) using measurements and a chosen estimator/switching logic.
2. Update the predictive model using Equation (26) and/or Equation (27).
3. Solve the constrained MPC problem Equations (23) and (24) with the updated model.
4. Apply $u_{opt}(0) \longrightarrow u(k)$, update estimates, and repeat.

3.2.2. Robust and Learning-Enhanced Tracking Under Uncertainty

Robust and learning-enhanced tracking MPC addresses model mismatch, external disturbances, parameter drift, and uncertain operating conditions. Across the reviewed studies, LPV/tube-based robust MPC, Gaussian Process residual modeling, tuning-parameter-free MPC, and two-layer learning-supported MPC all aim to preserve constraint satisfaction and tracking reliability when the nominal vehicle model is incomplete or changing [15,16,21,24,51,52]. Compared with nominal and adaptive tracking MPC, these formulations provide stronger protection against uncertainty, but they require credible uncertainty bounds, interpretable learned corrections, and evidence of real-time solvability.

Recent studies broaden robust tracking beyond disturbance rejection alone. Tire-adhesion-aware NMPC, curvature-dependent horizon adaptation, integrated spatial kinematics–dynamics MPC, and four-wheel-independent steering/driving control show that robustness increasingly depends on preserving stability when road friction, curvature, actuator effectiveness, or available control authority change [31–33,38,39]. In this sense, robust tracking is becoming a coordinated management problem involving lateral motion, longitudinal regulation, actuator allocation, and stability-related constraints.

The main cross-study lesson is that learning is most useful when it refines model-based prediction rather than replacing it. Residual correction, online parameter updates, and horizon adjustment rules can improve tracking under uncertainty, but the safety value of these methods depends on whether the learned component remains bounded, interpretable, and compatible with explicit MPC constraints.

Equations (28)–(32) summarize the main uncertainty representations used in robust and learning-enhanced tracking MPC: bounded additive disturbances, nominal/error decomposition, tightened admissible sets, learned residual dynamics, and GP-based uncertainty tightening.

$$x(k+1) = f(x(k), u(k)) + w(k), w(k) \in W \tag{28}$$

where $w(k)$ is an unknown but bounded disturbance and W is the associated uncertainty set.

A common robust decomposition separates the predicted state into a nominal component and an error component:

$$x(k) = \bar{x}(k) + e_x(k), e_x(k) \in \mathcal{E} \tag{29}$$

where $\bar{x}(k)$ is the nominal state and $\mathcal{E}$ is a robust error tube or invariant error set.

To preserve constraint satisfaction under bounded uncertainty, tightened admissible sets are often enforced on the nominal prediction:

$$\bar{x}(k) \in X \ominus \mathcal{E}, u(k) \in U \ominus K\mathcal{E} \tag{30}$$

where $\ominus$ denotes the Pontryagin difference and K is a feedback gain used to keep the actual trajectory within the robust tube.

Learning-enhanced MPC schemes often augment the nominal model with a data-driven residual term. A common GP-based representation is:

$$x(k+1) = f_{\text{nom}}(x(k), u(k)) + \mu_{GP}(x(k), u(k)) \tag{31}$$

where $f_{\text{nom}}(\cdot)$ is the nominal prediction model and $\mu_{GP}(\cdot)$ denotes the learned mean correction term.

To account for uncertainty in the learned residual model, tracking constraints can be tightened using the predictive variance:

$$x(k) \in X \ominus \beta\Sigma_{GP}(k) \tag{32}$$

where $\Sigma_{GP}(k)$ represents the *GP* uncertainty bound at step k and β is a confidence-scaling coefficient.

Algorithms 7 and 8 summarize how robust and learning-enhanced tracking MPC implements these uncertainty-handling mechanisms within the receding-horizon loop.

Algorithm 7: Robust tracking MPC (LPV/tube-based execution)

1. Build or update the prediction model using the disturbed dynamics in Equation (28) and the nominal error decomposition in Equation (29).
2. Propagate the nominal state $\overline{x}(k)$ and enforce tightened constraints using Equation (30).
3. Solve the nominal MPC problem in Equations (23) and (24) with the tightened admissible sets.
4. Apply the first optimized control input, update the uncertainty or tube bound $\mathcal{E}$ as needed, and repeat at the next control step.

Algorithm 8: Learning-enhanced tracking MPC (residual learning + MPC solve)

1. Using recent data, update the learned residual model μ_{GP} and the associated uncertainty measure.
2. Form the predictive model with the learned correction using Equation (31).
3. Apply uncertainty-aware constraint tightening using Equation (32).
4. Solve the MPC problem in Equations (23) and (24), apply the first optimized control input, and repeat at the next control step.

3.2.3. Comfort- and Context-Aware Formulations

Comfort- and context-aware tracking MPC extends conventional path following by including ride quality, steering smoothness, lateral acceleration, speed adaptation, and scenario-dependent tuning within the control objective. Across the reviewed studies, these formulations show that tracking accuracy alone is not sufficient for safe and acceptable AV behavior when the resulting motion is uncomfortable, unstable, or overly aggressive [2,34,36,40,47,61,100].

The main cross-study trend is the integration of comfort and context into the predictive control loop rather than treating them as secondary add-ons. Cost-function adaptation, curvature-aware prediction, fuzzy context switching, infrastructure-supported planning, and steering-actuation-aware control allow the controller to balance tracking accuracy, stability, comfort, and feasibility under changing road and traffic conditions.

A further trend is the coupling of lateral path tracking with longitudinal velocity or spacing regulation. Integrated path-and-velocity control and energy- or context-aware designs indicate that safer and smoother motion often requires proactive speed adaptation, especially during curvature transitions, vehicle following, or obstacle-constrained tracking [39,61,88,100].

Equations (33)–(38) summarize the main comfort- and context-aware extensions used in tracking MPC: comfort-augmented cost terms, input rate penalties, lateral acceleration approximation, context-dependent weighting, prediction horizon adaptation, and longitudinal spacing control.

$$J_c = \sum_{k=0}^{N-1} \left(e(k)^T Q e(k) + u(k)^T R u(k) + q_{\Delta u} \parallel \Delta u(k) \parallel_2^2 + q_r r(k)^2 + q_{a_y} a_y(k)^2\right) + e(N)^T P e(N) \quad (33)$$

where $q_{\Delta u}$, q_r, and q_{a_y} are non-negative weights assigned to input smoothness, yaw rate moderation, and lateral acceleration moderation, respectively.

The input rate term is defined as:

$$\Delta u(k) = u(k) - u(k-1) \tag{34}$$

which is commonly used to reduce jerky steering or acceleration changes.

A practical approximation of lateral acceleration used in path following formulations is:

$$a_y(k) \approx v(k)\, r(k) \tag{35}$$

where $v(k)$ is the longitudinal speed and $r(k)$ is the yaw rate.

Context-aware MPC can be represented by introducing a context or scheduling variable $\lambda(k)$ that modulates either the cost or the model:

$$J(k) = J_{\text{track}}(k) + \lambda_c(k) J_{\text{comfort}}(k) + \lambda_o(k) J_{\text{context}}(k), \quad \lambda(k) \in \Lambda \tag{36}$$

where Λ is the admissible context set and the coefficients $\lambda_c(k)$ and $\lambda_o(k)$ determine the relative importance of comfort- and context-dependent objectives.

When prediction horizon adaptation is used, the prediction length may be adjusted as a function of speed, curvature, or operating condition:

$$N_p(k) = \mathcal{N}(v(k), \kappa(k), \lambda(k)) \tag{37}$$

where $N_p(k)$ is the active prediction horizon and $\kappa(k)$ is the road curvature at step k.

In vehicle-following and platooning scenarios, longitudinal safety and tracking objectives are often enforced using a time headway spacing policy. The desired inter-vehicle spacing and the corresponding spacing error are defined as:

$$s_{\text{des}}(k) = s_0 + T_h v(k), e_s(k) = s(k) - s_{\text{des}}(k) \tag{38}$$

where $s(k)$ is the actual longitudinal spacing, $s_{\text{des}}(k)$ is the desired spacing, s_0 is the standstill distance, T_h is the time headway parameter, and $v(k)$ denotes the vehicle speed.

Algorithms 9 and 10 summarize how comfort penalties and context-dependent adaptation are incorporated into the tracking MPC loop.

Algorithm 9: Comfort-aware tracking MPC (objective augmentation)

1. Compute tracking error $e(k)$ using Equation (21) and construct the base MPC problem using Equations (23) and (24).
2. Compute comfort-related signals, including the input rate term $\Delta u(k)$ using Equation (34), yaw rate $r(k)$, and lateral acceleration $a_y(k)$ using Equation (35).
3. Augment the tracking objective with comfort penalties using Equation (33).
4. Solve the comfort-aware MPC problem, apply the first optimized input $u_{opt}(0) \rightarrow u(k)$, shift the horizon, and repeat.

Table 3a–c summarize the reviewed tracking-oriented MPC studies by technique and control objective. The main cross-study trade-off is between nominal tracking performance, robustness, comfort, and implementation complexity: nominal and adaptive MPC remains suitable for structured real-time tracking, robust and learning-enhanced MPC improves uncertainty handling at higher computational and modeling cost, and comfort- or context-

aware MPC improves motion acceptability but still requires stronger integration with safety metrics.

Algorithm 10: Context-aware tracking MPC (context evaluation and horizon adaptation)

1. Evaluate context variables such as vehicle speed $v(k)$, road curvature $\kappa(k)$, obstacle proximity, or uncertainty indicators.
2. Update the context-dependent weighting terms in Equation (36) and, when required, adapt the prediction horizon using Equation (37).
3. If longitudinal spacing is relevant, update the desired spacing and spacing error using Equation (38).
4. Solve the MPC problem with the updated context-dependent objective, constraints, and prediction horizon.
5. Apply the first optimized input, then re-evaluate the context at the next control update.

Table 3. (**a**). Summary of nominal and adaptive MPC techniques for trajectory tracking and path following. (**b**). Summary of robust and learning-enhanced MPC techniques for trajectory tracking and path following. (**c**). Summary of comfort and context-aware MPC techniques for trajectory tracking and path following.

(**a**)

Technique/Method	Ref.	Control Objective
Linear/nonlinear MPC	[7,42–44,46,53,54,59]	Real-time path tracking under nominal and nonlinear dynamics
Adaptive and hybrid MPC	[48,49,60]	Adapt to changing dynamics, sensor noise, or system modes
NMPC for vehicle following	[1,45]	Maintain relative distance and track curvature in platooning scenarios
Two-layer curvature-adaptive MPC	[72]	Improve high-speed path tracking by adapting to road curvature and prediction domain requirements
Path planning and predictive control for obstacle-constrained tracking	[1,38,61,87]	Couple reference path generation with predictive tracking under dynamic and obstacle-related constraints
Reliable and efficient path tracking with obstacle-aware cost shaping	[71]	Track the reference path while maintaining feasibility in the presence of static and dynamic obstacles
Time-varying and non-uniformly spaced horizon MPC	[36]	Extend look-ahead capability while preserving tracking accuracy and computational efficiency
NMPC with terminal cost for trajectory following	[35]	Improve tracking convergence and terminal stability in nonlinear path following tasks

Table 3. *Cont.*

(**b**)		
Technique/Method	**Ref.**	**Control Objective**
Robust MPC (RMPC, LPV)	[15,16,52,55–58]	Maintain tracking under disturbances and parameter variation
Gaussian Process-enhanced MPC	[21,24]	Compensate modeling error through learning-based residual correction
Parameter-free MPC with nonlinear IMC	[51]	Robust lateral path tracking under parameter changes and low-friction conditions without manual tuning of MPC weighting parameters
Tire-adhesion-aware NMPC	[31]	Preserve path-tracking performance under changing tire-force availability and high-demand maneuvers
Simultaneous drift and trajectory tracking MPC	[34]	Maintain tracking performance during aggressive maneuvers near handling limits
Integrated spatial kinematics-dynamics MPC	[32]	Improve collision-free trajectory tracking while accounting for lateral and roll-related dynamic constraints
Integrated path tracking and velocity control for four-wheel-independent actuation	[39]	Coordinate steering and wheel-torque allocation to improve path and velocity tracking under demanding road conditions
(**c**)		
Technique/Method	**Ref.**	**Control Objective**
Comfort-aware MPC	[2]	Improve passenger comfort by minimizing jerk and yaw rate
Fuzzy-logic-based context switching	[47]	Adapt tracking behavior to environmental or operational context
Online-updated MPC with fuzzy control and variable prediction horizon	[39]	Adapt controller weighting and prediction structure to speed and path tracking context
Online-updated MPC with fuzzy control and variable prediction horizon	[36]	Adapt controller weighting and prediction structure to speed and path tracking context
Energy-oriented path following and collision avoidance via NMPC	[37]	Balance path following quality, safety, and energy-aware control behavior
Integrated motion planning and control utilizing infrastructure sensor nodes	[33]	Use external context information to improve path following and motion planning in connected environments
Path tracking using steering torque	[100]	Improve smoothness and tracking performance through steering-actuation-aware control

Collectively, the embedded formulations in Equations (21)–(38) and Algorithms 5–10 map the reviewed tracking literature into implementable MPC components: nominal and adaptive prediction with horizon optimization (Section 3.2.1), robust and learning-enhanced uncertainty handling through tightening and residual modeling (Section 3.2.2), and comfort- and context-aware extensions through smoothness penalties, adaptive weighting, and integrated longitudinal–lateral objectives (Section 3.2.3).

3.3. Intersection and Coordination Tasks

Autonomous vehicle coordination at intersections, lane merges, roundabouts, and cooperative maneuvers creates challenges beyond single-vehicle control because safety depends on interaction timing, shared constraints, communication quality, and surrounding agent behavior. Across the reviewed studies, coordination-oriented MPC can be grouped into cooperative and predictive maneuvering, hierarchical and contract-based architectures, and centralized or mission-level planning. The cross-study trend is that coordination MPC has moved beyond simple trajectory exchange toward interaction prediction, merge gap evaluation, risk-sensitive negotiation, and shared longitudinal–lateral motion planning. Therefore, this domain is evaluated not only by conflict-free trajectory generation but also by scalability, communication assumptions, computational feasibility, and robustness to heterogeneous human-driven behavior.

Equations (39)–(41) summarize the common cooperative MPC structure used to compare coordination studies: individual vehicle dynamics, shared interaction costs, and agent-specific state/input constraints.

$$x_i(k+1) = f_i(x_i(k), u_i(k)) \tag{39}$$

where $x_i(k)$ and $u_i(k)$ denote the state and control input of vehicle i at step k, respectively, and $f_i(\cdot)$ represents the corresponding vehicle dynamics model.

Coordination among multiple vehicles is achieved by coupling individual objectives through shared cost terms or interaction penalties, resulting in a cooperative MPC optimization problem of the form:

$$\min_{\{u_i(0:N-1)\}_{i=1}^{N_v}} \sum_{i=1}^{N_v} \sum_{k=0}^{N-1} \left(\| x_i(k) - x_{i,\mathrm{ref}}(k) \|_{Q_i}^2 + \| u_i(k) \|_{R_i}^2 \right) + \sum_{k=0}^{N-1} \sum_{(i,j)\in\mathcal{E}} \Psi_{ij}(x_i(k), x_j(k)) \tag{40}$$

where N_v is the number of vehicles, $x_{i,\mathrm{ref}}(k)$ is the reference trajectory for vehicle i, Q_i and R_i are weighting matrices, $\mathcal{E}$denotes the set of interacting vehicle pairs, and $\Psi_{ij}(\cdot)$ represents interaction or safety coupling terms such as collision avoidance or precedence enforcement.

Cooperative optimization is subject to individual state and input constraints for each vehicle over the prediction horizon, expressed as:

$$x_i(k) \in X_i, u_i(k) \in U_i, k = 0, \ldots, N-1, \forall i \tag{41}$$

where X_i and U_i denote the admissible state and input sets associated with vehicle i.

3.3.1. Cooperative and Predictive Maneuvering

Cooperative and predictive maneuvering MPC extends safety reasoning from the ego vehicle to interacting with traffic participants. Across the reviewed studies, cooperative trajectory exchange, event-triggered communication, game-theoretic prediction, reachability analysis, and nonlinear cooperative MPC are used to coordinate merging, overtaking, intersection negotiation, turning, and roundabout maneuvers [3,4,8,10,11,73,76,77,82]. The

main safety contribution is anticipatory coordination: the controller plans not only around static constraints but also around expected interaction windows and feasible responses of nearby agents.

A key cross-study trend is the shift from pure trajectory sharing toward structured interaction modeling. Distributed cooperative path planning, human driver trajectory integration, merge gap management, connected platoon coordination, and intersection speed planning show that safe maneuvering often depends on predicting whether surrounding vehicles will create, preserve, or close feasible gaps [20,75,76,91,92]. This is especially important in mixed traffic, where the ego vehicle's safe action depends on both its own feasibility and the probable evolution of neighboring agents.

The main deployment limitation is dependence on communication quality, prediction accuracy, and solver update speed. Cooperative MPC can improve safety and traffic efficiency, but its reliability decreases when shared intent is delayed, surrounding vehicles behave unexpectedly, or the local optimization cannot update fast enough for changing interaction conditions.

Equations (42)–(46) group the main interaction safety mechanisms used in cooperative and predictive MPC: inter-vehicle separation, merge gap constraints, event-triggered communication, best-response interaction modeling, and reachability-based coordination. For inter-vehicle separation, the distance $d_{ij}(k)$, computed from the planar positions $p_i(k)$ and $p_j(k)$, is required to remain above a minimum allowable separation $d_{\min}$, i.e.,

$$d_{ij}(k) = \| p_i(k) - p_j(k) \|_2 \geq d_{\min} \tag{42}$$

where $d_{ij}(k)$ is the distance between vehicles i and j at step k, $p_i(k)$ is the position of vehicle i, and $d_{\min}$ is the minimum allowable separation.

In coordinated merging and lane-change settings, coupling between agents can also be represented through relative gap constraints, where the available gap $g_{ij}(k)$ must satisfy a required target gap $g_{ij}^{\text{des}}(k)$, i.e.,

$$g_{ij}(k) \geq g_{ij}^{\text{des}}(k) \tag{43}$$

where $g_{ij}(k)$ denotes the available longitudinal or spatiotemporal gap between interacting vehicles and $g_{ij}^{\text{des}}(k)$ is the required safe gap, which may vary with speed, context, or priority.

To reduce communication burden in decentralized implementations, event-triggered coordination strategies transmit updated information only when the deviation from the last communicated state exceeds a threshold. A standard event-triggering rule can be written as:

$$\text{Transmit}_i \iff \| x_i(k) - x_i\left(k_i^{\text{last}}\right) \| > \delta_i \tag{44}$$

where k_i^{last} denotes the most recent communication instant for vehicle i, and δ_i is the triggering threshold.

In game-theoretic or interaction-aware MPC, each vehicle's decision depends on the predicted behavior of surrounding agents. A generic best-response formulation can be expressed as:

$$u_{i,\text{opt}} = \arg \min_{u_i(0:N-1)} J_i(u_i, \hat{u}_{-i}) \tag{45}$$

where $J_i(\cdot)$ is the objective of vehicle i and $\hat{u}_{-i}$ denotes the predicted actions of the other agents.

Reachability-based coordination methods often enforce that the future joint state remains inside a safe multi-agent set, expressed as:

$$x(k) \in \mathcal{S}_{\text{coord}}, k = 0, \ldots, N \tag{46}$$

where $\mathcal{S}_{\text{coord}}$ denotes a safe coordination set that excludes collision, precedence violation, or infeasible merge or intersection configurations.

Algorithms 11 and 12 summarize how cooperative MPC combines trajectory or intent exchange with event-triggered communication during decentralized coordination.

Algorithm 11: Decentralized cooperative MPC with trajectory/intent exchange

1. Each vehicle i measures $x_i(k)$ and receives predicted trajectories or intents from neighbors $j \in \mathcal{N}_i$.
2. Vehicle i formulates a local MPC problem using Equations (39)–(41), including coupling terms $\Psi_{ij}(\cdot)$ and safety constraints such as Equations (42) and (43).
3. Solve for the optimal input sequence $u_{i,opt}(0 : N-1)$ and apply only the first control input $u_{i,opt}(0) \longrightarrow u_i(k)$.
4. Share the updated predicted trajectory or intent with neighboring vehicles, either continuously or according to the event-triggered rule in Algorithm 12, then shift the horizon and repeat.

Algorithm 12: Event-triggered coordination layer for cooperative MPC

1. For each vehicle i, compute deviation $e_i(t)$ between predicted and observed neighbor information.
2. If the triggering condition in Equation (44) is satisfied, transmit the updated state, predicted trajectory, or intent information to neighboring vehicles $\mathcal{N}_i$.
3. If the triggering condition is not satisfied, retain the previously communicated information to reduce communication load.
4. Re-solve the local MPC problem with the latest available neighbor information and apply the first optimized input.

3.3.2. Hierarchical and Contract-Based Control Architectures

Hierarchical and contract-based MPC architectures address coordination complexity by separating strategic decisions from low-level dynamically feasible control. Across the reviewed studies, high-level scheduling, contract negotiation, GP-supported dynamic constraints, and lower-level MPC tracking are used to manage intersections, roundabouts, merging, and mixed-traffic coordination while preserving interpretability and feasibility [8,20,24,63,65,73,77,91].

The main cross-study trend is tighter integration between planning, scheduling, speed regulation, and local MPC tracking. Instead of treating coordination as a separate planning problem, recent hierarchical approaches use upper layers to define right-of-way, merging order, passage windows, or feasible constraint sets, while lower layers generate steering and acceleration commands that satisfy vehicle dynamics and safety constraints.

The main limitation is consistency between layers. Safety depends on whether high-level schedules, negotiated contracts, predicted human driver behavior, and low-level feasibility constraints remain mutually compatible under changing traffic conditions, communication delays, and mixed-autonomy behavior.

Equations (47)–(50) group the main hierarchical and contract-based coordination mechanisms used in the reviewed studies: high-level scheduling, schedule-constrained low-level MPC, contract set definition, and contract-constrained feasibility enforcement.

$$\sigma_{opt} = \arg \min_{\sigma \in \Sigma} J_{\text{sched}}(\sigma) \tag{47}$$

where Σ denotes the set of admissible schedules and $J_{\text{sched}}(\sigma)$ is a scheduling objective that may capture delay, conflict reduction, or throughput.

Given the selected schedule, the low-level controller solves a constrained MPC problem that respects the schedule-induced feasible set $X(\sigma)$:

$$\min_{u(0:N-1)} J \text{s.t. } x(k) \in X(\sigma), u(k) \in U, k = 0, \ldots, N-1 \tag{48}$$

where $X(\sigma)$ is the admissible state set induced by the selected coordination or scheduling decision.

Contract-based hierarchical MPC further improves modularity by negotiating admissible constraint sets between layers. This negotiation can be expressed by defining a contract set $\mathcal{C}$ as:

$$\mathcal{C} = \{\text{constraints on } x(k), u(k) \text{ agreed between planner and controller}\} \tag{49}$$

where $\mathcal{C}$ denotes the agreed specification between modules, defining required conditions on states and/or inputs.

The controller then enforces feasibility by solving the MPC problem under both the baseline constraints and the negotiated contract constraints, written as:

$$u(0:N-1) \text{s.t. } x(k) \in X \cap \mathcal{C}, u(k) \in U \cap \mathcal{C}, \forall k \tag{50}$$

where optimization enforces both the baseline sets (X, U) and the contract set $\mathcal{C}$ across the horizon.

Algorithms 13 and 14 summarize how hierarchical MPC links high-level scheduling or contract negotiation with low-level feasibility checking and control execution.

Algorithm 13: Hierarchical MPC for intersection coordination

1. High-level layer computes schedule σ (e.g., time slots/order) by solving Equation (47).
2. Low-level layer solves the constrained MPC in Equation (48) to generate dynamically feasible trajectories respecting $X(\sigma)$.
3. Apply the first control input; update schedule and repeat.

Algorithm 14: Contract-based hierarchical MPC (negotiation + control)

1. Planner proposes a contract set $\mathcal{C}$ defining admissible bounds/constraints for tracking and coordination.
2. Controller checks feasibility of the MPC problem under $X \cap \mathcal{C}$ and $U \cap \mathcal{C}$.
3. If infeasible, refine $\mathcal{C}$ (tighten/relax agreed bounds) and repeat Step 2.
4. Once feasible, solve MPC and apply the first input; update contracts as conditions change.

3.3.3. Centralized and Mission-Level Planning

Centralized and mission-level MPC coordinates multiple AVs through shared optimization, global state information, or upper-level maneuver reasoning. Across the reviewed studies, these approaches are most useful in structured or infrastructure-supported scenarios such as area coverage, roundabouts, overtaking, merge coordination, and unsignalized

intersections, where safe motion depends on passage timing, conflict ordering, right-of-way usage, and interaction with multiple surrounding vehicles [8,20,64,73,74,95,101].

The main cross-study strength of centralized planning is its ability to optimize conflict-zone timing and multi-vehicle behavior explicitly. This can improve global consistency and reduce collision risk in structured traffic layouts. However, the same feature creates the main limitation: centralized MPC becomes less practical as the number of vehicles, communication load, and uncertainty in agent behavior increase.

Mission-level planning is therefore most valuable when it shapes the feasible interaction strategy that lower-level controllers will track, for example, by evaluating whether overtaking is admissible, when a vehicle should enter a roundabout, or how an unsignalized intersection should be crossed. Its practical value depends on whether the upper-level plan remains compatible with real-time local control under limited visibility, uncertain intent, and changing traffic conditions.

Equations (51) and (52) summarize the centralized mission-level MPC pattern used in the reviewed studies: aggregated multi-agent state prediction and joint optimization of tracking and control effort under shared coordination constraints.

$$X(k+1) = F(X(k), U(k)) \tag{51}$$

where $X(k)$ is the aggregated global state, $U(k)$ is the aggregated global input, and $F(\cdot)$ is the global transition function describing the coupled multi-agent dynamics.

The corresponding centralized optimization is then posed by minimizing a quadratic tracking-and-effort objective over the horizon, expressed as:

$$\min_{U(0:N-1)} \sum_{k=0}^{N-1} \left(\| X(k) - X_{\text{ref}}(k) \|_Q^2 + \| U(k) \|_R^2 \right) \tag{52}$$

where $U(0:N-1)$ denotes the joint input sequence, $X_{\text{ref}}(k)$ is the reference aggregated trajectory, and Q and R are weighting matrices defining the tracking and control effort penalties, respectively.

Algorithm 15 summarizes how centralized MPC performs global optimization and distributes the first-step control actions to participating vehicles.

Algorithm 15: Centralized multi-agent MPC (global optimization)

1. Collect states $x_i(k)$ from all vehicles and form the joint state $X(k)$.
2. Build the centralized model (Equation (51)) and constraints (including multi-vehicle safety and mission constraints).
3. Solve the centralized optimization (Equation (52)) over the horizon.
4. Distribute and apply the first input $u_i(k)$ for each vehicle; update and repeat.

Table 4a–c summarize the coordination-oriented MPC studies by technique and control objective. The main cross-study trade-off is between global optimality, modularity, and deployability: centralized MPC can improve global consistency but scales poorly with agent number and communication load; distributed and cooperative MPC improves scalability but depends on reliable intent exchange and prediction; and hierarchical or contract-based MPC improves modularity but requires consistency between planning and control layers.

Table 4. (**a**). Summary of cooperative and predictive maneuvering MPC techniques for intersection and coordination tasks. (**b**). Summary of hierarchical and contract-based MPC techniques for intersection and coordination tasks. (**c**). Summary of centralized and mission-level planning MPC techniques for intersection and coordination tasks.

(**a**)

Technique/Method	Ref.	Control Objective
Cooperative MPC (C-MPC)	[3,4]	Synchronized lane changes and merging via trajectory sharing
Event-triggered coordination	[82]	Minimize communication by triggering only on significant deviation
Game-theoretic and reachability MPC	[10,11]	Ensure safety in multi-agent environments through behavior prediction
Roundabout MPC control strategies	[75,95]	Coordinate entry, circulation, and merge behavior in roundabout traffic while preserving collision-free motion
Cooperative trajectory planning using nonlinear MPC	[90]	Coordinate multi-vehicle trajectories through shared predictive planning and collision-aware optimization
Automated turning and merging using nonlinear MPC	[18]	Generate safe turning and merging maneuvers under dynamic interaction constraints
Vehicle platooning for merge coordination using hybrid ACC-DMPC	[73]	Improve merge efficiency and safety in connected driving environments through coordinated platoon control
Enhanced adaptive cruise control in connected vehicle environments	[76]	Support safe longitudinal coordination and spacing control in connected multi-vehicle traffic
Distributed nonlinear MPC for connected platoons with distance-dependent air drag	[77]	Coordinate platoon motion under coupled aerodynamic effects while preserving spacing and stability

(**b**)

Technique/Method	Ref.	Control Objective
Hierarchical MPC for intersection coordination	[65]	Separate scheduling and control for scalable coordination
Contract-based hierarchical MPC	[63]	Ensure compatibility between planner and controller via constraint negotiation
GP-supported MPC constraints	[24]	Improve feasibility and robustness by adapting dynamic constraints under model mismatch
Distributed cooperative path planning integrating human driver trajectories	[91]	Coordinate autonomous vehicle motion while explicitly accounting for predicted human driver behavior
Driver risk-perception-based trajectory planning	[78]	Incorporate human-like gap acceptance and subjective risk behavior into coordinated maneuver planning
Intersection speed planning with MPC-based trajectory tracking	[89]	Combine speed planning and lower-level tracking for structured intersection negotiation

(**c**)

Technique/Method	Ref.	Control Objective
Centralized multi-agent MPC	[64]	Allocate and coordinate multi-vehicle tasks under a unified planning framework
Roundabout mission-level timing and speed regulation	[8,73]	Optimize right-of-way usage, circulation timing, and conflict zone traversal in structured roundabout environments

Table 4. *Cont.*

(c)		
Technique/Method	**Ref.**	**Control Objective**
Risk-aware overtaking and trajectory planning on two-lane roads	[101]	Evaluate overtaking risk and generate globally feasible maneuvers under opposing traffic interaction
High-speed overtaking in structured environments using robust MPC	[20]	Plan dynamically feasible overtaking maneuvers through upper-level conflict evaluation and trajectory selection
Learning-based stochastic MPC for unsignalized intersections	[23]	Couple interaction-aware state inference with motion planning for safe and efficient intersection crossing

4. Cross-Cutting Challenges

The reviewed literature confirms that MPC is a powerful framework for AV safety, but it also exposes several recurring weaknesses that limit confidence in deployability. These weaknesses are not isolated to one subfield; they appear across collision avoidance, tracking, and coordination studies. They are particularly important for safety-oriented MPC because a formulation that is mathematically safe may still be difficult to deploy if it cannot handle perception uncertainty, solver delays, communication limits, or actuator constraints within the required real-time control cycle.

The first challenge is computational credibility. Many papers propose richer nonlinear, stochastic, or multi-agent formulations without providing enough evidence that the resulting optimization problems can be solved reliably within the time budgets required by safety-critical driving. Solver choice, horizon length, warm-start strategy, and worst-case execution time are often underreported. This makes it difficult to judge whether the reported safety benefits would persist under realistic sampling times, embedded hardware limitations, emergency maneuvers, or sudden changes in obstacle behavior.

The second challenge is uncertainty treatment. A large share of the literature acknowledges uncertainty in perception, prediction, tire–road interaction, or surrounding agent intent, but fewer papers show how uncertainty propagates through the controller in a way that preserves interpretable safety guarantees. In many cases, robustness is asserted more strongly than it is demonstrated. This gap is especially important in mixed traffic, where safety depends not only on the ego vehicle model but also on uncertain pedestrian behavior, human driver intent, occlusion, sensor noise, and rapidly changing road friction.

The third challenge is fragmented architecture. Perception, prediction, planning, communication, and low-level control are still frequently studied as loosely connected modules. This separation is convenient for analysis, but it weakens claims of end-to-end safety because errors originating upstream are often simplified away before reaching the MPC formulation. For deployable AV systems, safety analysis should therefore account for how perception errors, delayed predictions, map uncertainty, and actuator limitations influence the feasibility and reliability of the MPC solution.

The fourth challenge is scalability in interactive traffic. Cooperative and distributed MPC methods are promising, yet their performance can degrade quickly as the number of agents, communication delays, or behavioral uncertainties increase. Several coordination papers remain convincing only in small or highly structured scenarios. This limitation is particularly relevant for intersections, merges, roundabouts, and dense urban traffic, where safety depends on multiple interacting agents and where centralized or fully cooperative assumptions may not hold.

These challenges can be summarized through four recurrent system-level limitations:

- Scalability of optimization: strongly coupled formulations become difficult to solve or certify as scenario complexity grows.
- Communication fragility: decentralized cooperation is sensitive to packet loss, stale intent exchange, bandwidth limits, and asynchronous updates.
- Incomplete modeling of agent intent: many methods still rely on simplified assumptions about surrounding drivers, pedestrians, or mixed-autonomy behavior.
- Validation imbalance: simulation studies dominate, while hardware, vehicle-level experiments, and standardized safety metrics remain limited.

To make this validation gap more explicit, Table 5 summarizes the validation maturity levels observed across the reviewed safety-oriented MPC studies. The table is qualitative rather than count-based because the included papers report validation evidence with different levels of detail and non-uniform terminology.

Table 5. Validation maturity levels in reviewed safety-oriented MPC studies.

Validation Maturity Level	Typical Evidence in Reviewed Studies	Engineering Interpretation
Simulation-only validation	Controller tested in numerical simulation, often with simplified vehicle, traffic, or sensing assumptions.	Useful for initial feasibility but limited for assessing deployment readiness.
Scenario-based simulation	Controller evaluated under lane-changing, overtaking, intersection, pedestrian, or disturbance scenarios.	Improves safety relevance, but results remain sensitive to scenario design and assumptions.
Computation time reporting	Details such as average solver time, sampling time, horizon length, or solver configuration are reported.	Provides partial evidence of real-time feasibility, but worst-case timing is often missing.
Software-in-the-loop or hardware-in-the-loop validation	Controller tested with more realistic software, embedded hardware, or real-time simulation environments.	Strengthens implementation credibility but remains less common than pure simulation.
Experimental or vehicle-level testing	Controller evaluated on a physical platform or vehicle-scale experimental setup.	Provides stronger deployment evidence but appears only in a limited part of the literature.
Real-time deployment evidence	Controller demonstrates feasible closed-loop operation with timing, sensing, actuation, and fallback considerations.	Represents the strongest maturity level but is still underreported across safety-oriented MPC studies.

From an engineering perspective, these limitations show that safety-oriented MPC should be evaluated not only by formulation or simulation performance but also by implementation evidence. Future studies should report solver type, sampling time, prediction horizon, hardware platform, average and worst-case computation time, warm-start strategy, infeasibility handling, and fallback control logic. Such reporting would make it easier to distinguish improvements caused by the MPC formulation itself from improvements caused by vehicle model fidelity, scenario design, solver configuration, or evaluation assumptions.

Taken together, these observations indicate that future progress depends not only on better optimization formulations but also on stronger evidence, more disciplined benchmarking, and tighter integration between controller design and realistic validation.

5. Future Research Directions

Future research on safety-oriented MPC should move from isolated controller refinements toward integrated, validation-aware system architectures. Across the three thematic domains, the most important directions are uncertainty-aware safety, bounded learning support, computation-aware design, standardized validation, and scalable interaction handling.

5.1. Risk-Sensitive and Adaptive Collision Avoidance

Future collision-avoidance research should move beyond nominal obstacle clearance toward uncertainty-aware emergency control that remains feasible under strict real-time limits. The most promising direction is hybrid robust-learning MPC, where model-based constraints define the safety envelope and data-driven components support prediction refinement, residual correction, or context adaptation without obscuring the safety logic.

Priority should also be given to computation-aware and interaction-aware design. Future studies should report solver timing, fallback behavior, degraded-operation logic, and controller response under perception loss, occlusion, intent uncertainty, mixed-autonomy behavior, or rapidly changing maneuver space.

5.2. Robust, Transparent, and Comfort-Aware Trajectory Tracking

Future trajectory tracking research should emphasize robust and interpretable adaptation that integrates tracking precision with comfort, fault tolerance, friction variation, and uncertainty-aware constraint handling. Learning-enhanced models should be evaluated with explicit safeguards and uncertainty bounds, while integrated lateral–longitudinal formulations should be tested under aggressive maneuvers, low-friction conditions, actuator limits, and disturbance recovery. Future studies should report comfort- and safety-related metrics together, including tracking error, lateral acceleration, jerk, yaw rate variation, constraint violation, computation time, and recovery behavior after disturbances.

5.3. Scalable and Interaction-Aware Coordination

Future coordination-oriented MPC should prioritize communication-resilient distributed architectures, interaction-aware prediction, and hierarchical decompositions that remain tractable as the number of agents increases. Coordination schemes should avoid assuming perfect cooperation or fully known intent; instead, they should represent negotiation, behavioral diversity, communication delay, packet loss, asynchronous updates, and imperfect intent prediction within the evaluation framework.

Standardized validation is also essential for this domain. Common scenario families, clearer safety metrics, and stronger reporting of computation and experiment design would make it easier to compare coordination methods and judge whether they can transfer from small, idealized networks to realistic mixed traffic.

In summary, future safety-oriented MPC research should combine model-based guarantees, uncertainty-aware prediction, bounded learning support, scalable coordination, and validation practices that more closely reflect real deployment conditions.

6. Conclusions

This paper reviewed 101 studies on safety-oriented MPC for autonomous vehicles and organized the evidence into three main domains: collision avoidance and risk mitigation,

trajectory tracking and path following, and intersection/coordination tasks. The review confirms that MPC remains one of the most versatile control frameworks for AV safety because it can unify prediction, optimization, and constraint handling within a single decision structure.

At the same time, the literature is stronger in methodological diversity than in validation depth. The field has progressed from nominal and geometry-based designs toward robust, risk-aware, hierarchical, and learning-enhanced architectures, but many published gains are still demonstrated primarily in simulation and under non-uniform evaluation settings.

The most important barriers to deployment are recurring rather than isolated: limited real-time evidence for complex formulations, incomplete treatment of uncertainty, fragmented integration of perception and control, and weak scalability of cooperative schemes in realistic interactive traffic. These limitations show that the maturity of safety-oriented MPC should be judged not only by theoretical formulation or simulation performance but also by real-time feasibility, uncertainty propagation, system integration, and reproducible validation practice.

Accordingly, future research should prioritize hybrid system architectures that preserve interpretable safety logic while incorporating richer prediction, bounded learning support, and scalable coordination. Progress will depend not only on designing better MPC algorithms, but also on reporting stronger evidence through more rigorous benchmarking and more realistic validation.

Overall, this review provides a tightened synthesis of the current state of safety-oriented MPC for AVs and identifies the methodological shifts, persistent weaknesses, and most credible research directions for safer and more deployable autonomous driving systems.

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