

Observer-Based Robust Model Predictive Control for Safe Trajectory Tracking of Autonomous Vehicles Under Dynamic Constraints

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Abstract

The safe deployment of autonomous vehicles depends on control architectures that can simultaneously manage uncertain state information, actuator limitations, environmental disturbances, and time-varying operational constraints. This paper presents a system-level examination of observer-based robust model predictive control for trajectory tracking under dynamic constraints. The discussion integrates estimation theory, constrained predictive control, and reachability-based safety reasoning to analyze how observer dynamics and robust constraint handling interact within a unified control framework. Rather than focusing on a single algorithmic derivation, the paper highlights architectural trade-offs among state reconstruction accuracy, computational complexity, actuator authority, and safety margin management. The analysis covers dynamic envelope constraints that adjust with road geometry, friction conditions, obstacle motion, and vehicle state, as well as the structural implications of embedding these constraints in real-time optimization. Deployment concerns such as embedded computation, communication latency, sensor fusion, and fail-operational behavior are examined in relation to functional safety standards. The paper further considers validation approaches, fairness across heterogeneous road users, and policy implications for certification and regulatory oversight. Through this interdisciplinary perspective, the paper argues that observer-based robust model predictive control should be understood not solely as a numerical control method but as a socio-technical system requiring coordinated design across estimation, optimization, infrastructure, governance, and safety assurance.

Keywords

autonomous vehicles; model predictive control; observer-based estimation; dynamic constraints; robust control; trajectory tracking; system safety.

1. Introduction

Autonomous vehicle operation has evolved from basic lane keeping into a complex control problem that couples perception uncertainty, environmental variability, and stringent safety requirements. Model predictive control has become a central methodology for trajectory

tracking because it can incorporate future predictions, actuator constraints, and explicit performance objectives in a receding horizon formulation [1]. The theoretical foundations of constrained predictive control emphasize recursive feasibility and stability under nominal conditions, but real vehicles operate far beyond nominal assumptions [2]. Early applications to autonomous steering demonstrated the capacity of predictive control to handle nonlinear vehicle dynamics and road constraints, while also revealing sensitivity to state estimation errors and model mismatch [3]. These limitations motivate more robust formulations that combine predictive optimization with observer-based state reconstruction and dynamic constraint management.

The central challenge is that trajectory tracking for autonomous vehicles cannot assume exact knowledge of vehicle states, tire forces, road geometry, or surrounding obstacles. State estimators and robust predictive controllers must therefore cooperate to ensure that control decisions remain safe even when measurement signals are degraded or delayed. Observer design introduces a structural dependency between estimation accuracy and control performance, and this dependency becomes more pronounced when the operational envelope changes rapidly due to curvature, surface conditions, or traffic interactions [4][5][6]. In this context, dynamic constraints are not fixed bounds but are generated from environment perception and vehicle capability models, and they must be propagated through the prediction horizon with an explicit representation of uncertainty.

This paper adopts a systems perspective rather than a narrowly algorithmic one. It examines observer-based robust model predictive control as an integrated architecture in which state estimation, constraint generation, optimization, and safety monitoring interact across multiple timescales. The discussion addresses structural trade-offs, computational governance, deployment constraints, validation, fairness, and regulatory implications. By linking control-theoretic concepts to system-level concerns, the paper aims to clarify how robust trajectory tracking can be designed not only for nominal performance but also for trustworthy operation in real infrastructure.

2. System Architecture and Problem Context

An autonomous vehicle control stack typically separates perception, prediction, planning, and control, but safety-critical trajectory tracking requires tight coupling among these layers. Robust nonlinear predictive control approaches have demonstrated significant advantages in stabilizing vehicles near handling limits, but they also impose heavier computational loads and require reliable estimates of lateral and longitudinal states [7]. Observer-based estimation becomes essential because direct measurement of sideslip angle, tire forces, and road friction is typically impractical or too costly for production systems [8]. The selection of an observer architecture involves trade-offs among convergence rate, robustness to parameter uncertainty, computational burden, and formal guarantees [9]. In this architecture, the observer does not merely supply state estimates to the controller; it also propagates estimation uncertainty forward through the prediction horizon, thereby shaping the degree of conservatism that the robust controller must adopt.

From a system-level perspective, the interaction between estimation and predictive control is bidirectional. Control actions affect the quality of future measurements by altering vehicle motion, while estimation residuals can reveal model mismatch or sensor degradation. A poorly tuned observer can inject spurious high-frequency components into the control signal, whereas an overly conservative robust controller can reduce observer excitation and degrade

state observability. These effects are especially evident during emergency maneuvers where tire forces saturate and road surface conditions change abruptly. The dynamic envelope concept therefore requires a coordinated treatment of estimation and constraint generation rather than a sequential pipeline.

3. Robust Predictive Control with Dynamic Constraints

Dynamic constraint generation in autonomous vehicles increasingly relies on heterogeneous data sources that include road geometry maps, weather services, vehicle-to-infrastructure messages, and historical traffic patterns. Cross-domain modeling approaches have shown that transferable features can improve prediction accuracy under limited local data, which is directly relevant to generating context-aware dynamic envelopes [10]. These data-driven predictions must be fused with physical vehicle models because errors in predicted road friction or obstacle motion directly propagate into constraint boundaries. The controller therefore requires a robust formulation that can maintain recursive feasibility and constraint satisfaction in the presence of bounded disturbances.

Robust model predictive control has developed along several complementary lines. Early robust formulations relied on linear matrix inequality techniques to guarantee stability and constraint satisfaction for polytopic uncertainties [11]. Tube-based methods constructed invariant sets around nominal trajectories and ensured that the actual state remained within a bounded neighborhood of the nominal prediction despite disturbances [12]. Constraint tightening then became a standard mechanism to preserve margins against persistent disturbances without solving an infinite-dimensional min-max problem at each step [13]. These approaches are attractive for automotive applications because they can be implemented with moderate real-time computation, but they require careful characterization of disturbance sets and can become overly conservative if the bounds are poorly estimated.

For vehicle dynamics, however, linear robust formulations are often insufficient because tire forces and yaw dynamics exhibit strongly nonlinear behavior near handling limits [14]. Nonlinear model predictive control offers higher fidelity and better performance but introduces nonconvex optimization and challenges in distributed implementation [15]. The dynamic envelope must therefore be represented not as fixed lateral acceleration or steering bounds but as a state-dependent set that shrinks when friction is low, expands when road geometry allows, and shifts when obstacles appear. This representation must be updated at the same rate as the control loop while remaining compatible with real-time solvers.

4. Safety Standards and Feasibility Governance

Functional safety standards for road vehicles emphasize the need to avoid unreasonable risk from systematic and random failures [16]. The SAE levels of driving automation further clarify the division of responsibility between human drivers and automated systems [17]. Within this governance frame, observer-based robust model predictive control is not only a numerical scheme but also a safety mechanism whose failure modes must be analyzed with the same rigor as actuators and brakes. Recursive feasibility, a central concept in constrained predictive control, corresponds at the system level to the ability of the vehicle to maintain a nonempty safe control set throughout the maneuver. If state estimation uncertainty grows, the feasible set may shrink, and the controller must choose between reduced tracking accuracy and increased safety margin.

The standards do not prescribe a specific algorithm, but they demand evidence that the system remains safe under specified fault and disturbance scenarios. For an observer-based controller,

this means that the interaction between estimator divergence and constraint violation must be explicitly addressed. A transient loss of global positioning information, for example, may increase lateral position uncertainty, which in turn reduces the allowable steering authority. The control architecture must therefore include a supervisory layer that can detect degraded estimation quality and switch to a more conservative dynamic envelope without abrupt discontinuities in control effort.

5. Observer-Based Integration and Dynamic Envelope Management

Recent work has integrated observer-based estimation with robust predictive control and dynamic envelopes to address the combined problem of uncertain state information and state-dependent constraints [18]. This line of research demonstrates that the dynamic envelope can be formulated to change with vehicle states, road boundary curvature, and obstacle motion while the observer provides bounded error estimates used to tighten constraints. Rather than treating estimation and constraint generation as separate modules, an integrated architecture shares uncertainty representations and develops a common parameterization for robust feasibility. The resulting control system is better able to handle scenarios such as a rapid lane change on a wet road where lateral acceleration limits are lower than nominal and sideslip angle estimates are critical to avoid loss of control.

Such integrated designs reveal an important structural trade-off. Tightening constraints based on worst-case estimation error increases robustness but may leave little actuator authority for tracking in narrow corridors. Conversely, if the observer is assumed precise without formal bounds, the controller may command aggressive steering that exceeds the available tire force when the true state differs from the estimated state. Dynamic envelope management must therefore balance conservatism and performance by updating uncertainty margins according to current sensing conditions, map confidence, and vehicle health. This balance is not fixed; it varies continuously with environmental complexity and with the operational design domain.

6. Deployment and Embedded Infrastructure

Deploying observer-based robust model predictive control in production vehicles involves software architecture, real-time scheduling, and sensor fusion across cameras, radar, lidar, and inertial measurement units. A comprehensive survey of motion planning and control techniques highlights the need for modular architectures that preserve safety across heterogeneous urban scenarios [19]. Online verification methods based on reachability analysis provide an additional layer of assurance by computing future occupancy sets and checking whether they intersect with obstacles under bounded disturbances [20]. These methods complement predictive control rather than replace it, but they require consistent disturbance models and may double the computational burden if not carefully designed.

From an infrastructure perspective, the dynamic envelope is not solely generated onboard. Roadside units, cloud-based map services, and vehicle-to-everything communication can supply preview information about curvature, surface quality, and traffic conflicts. This external information reduces local estimation uncertainty but introduces latency and data trust issues. The control system must therefore apply a form of temporal discounting: information that arrives with greater delay or lower confidence should receive less influence over the prediction horizon. This governance of information flow is as important as the numerical solver when the vehicle operates in mixed traffic with vulnerable road users.

7. Validation, Fairness, and Policy Implications

Validation of observer-based robust model predictive control cannot rely solely on aggregate benchmark performance. Because the system makes decisions under uncertain state information, validation campaigns must include adversarial scenarios that stress the observer, such as sensor dropout during high-curvature tracking, adversarial road surface changes, and ambiguous obstacle behavior. The interaction between estimation error and constraint violation must be measured across diverse road geometries, weather conditions, and traffic densities. A control architecture that performs well on highway scenarios may fail in dense urban environments where pedestrians and cyclists create rapidly moving dynamic constraints.

Fairness considerations arise when dynamic envelopes are generated from predictive models trained on heterogeneous road user data. If constraint generation systematically underestimates the stopping distance or acceleration capability of certain vehicle classes, the control system may allocate road space unevenly. Observer-based robust control can mitigate some of this bias by enforcing conservative envelopes around uncertain users, but the underlying data used to predict their behavior must be governed by transparent and auditable processes. Cross-domain predictive models, such as those used for traffic flow estimation, must be evaluated not only for accuracy but also for their distributional effects across different road users [10].

Policy implications extend to certification and post-deployment monitoring. Regulators may require manufacturers to specify the exact disturbance bounds assumed by the robust controller and the observer convergence guarantees under those bounds. This specification would enable independent auditors to evaluate whether a given dynamic envelope is appropriate for a given operational design domain. Post-deployment monitoring could collect near-miss events and estimation residuals to update safety margins without waiting for collisions. Such a feedback loop between field data and control architecture reflects a broader shift from static type approval to continuous safety assurance in automated driving.

The computational governance of observer-based robust model predictive control also intersects with sustainability. Real-time optimization consumes electrical energy and generates heat, particularly when nonlinear solvers and moving horizon estimators run simultaneously on embedded hardware. Efficient implementation requires model reduction, warm starting, and careful scheduling between estimation and control tasks. Overly frequent re-linearization or unnecessarily long prediction horizons can increase energy consumption without proportional safety benefits. System-level design should therefore treat computational effort as a constrained resource and evaluate sustainability trade-offs alongside safety and tracking performance.

8. Conclusion

Observer-based robust model predictive control provides a principled framework for safe trajectory tracking under dynamic constraints, but its effective deployment requires more than numerical control design. The interaction between state estimation, constraint generation, and predictive optimization creates a tightly coupled system whose performance depends on how uncertainty is represented, propagated, and governed across multiple timescales. Architectural choices about observer type, robust formulation, and dynamic envelope management determine not only tracking accuracy but also the system capacity to maintain recursive feasibility under real-world disturbances.

This paper has examined the systemic dimensions of such controllers, including estimation uncertainty, robust constraint tightening, real-time implementation, embedded infrastructure,

validation, fairness, and regulatory oversight. By treating observer-based robust model predictive control as a socio-technical system, it becomes possible to align control-theoretic rigor with the broader demands of trustworthy autonomous vehicle deployment. Future research should continue to integrate formal safety guarantees with data-driven environment modeling, while ensuring that dynamic constraints remain transparent, auditable, and fair across the full range of road users and operational conditions.

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