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SURVEY

Model predictive control: past, present, and future

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Abstract

Model predictive control (MPC) has evolved from an industry-originated heuristic to a rigorously grounded and widely adopted control framework. This survey provides a structured account of MPC's trajectory across three interrelated dimensions: theoretical foundations, practical deployments, and future outlook. We first trace the emergence of core principles especially around stability and robustness and highlight pivotal contributions that have shaped linear, nonlinear, robust, stochastic, and adaptive MPC variants. The second part reviews computational advances, data-driven innovations, and widespread deployments, with a particular emphasis on automotive applications. Finally, we articulate a forward-looking vision of MPC as a general and unified paradigm for embodied intelligence. Throughout, we underscore contributions from international and Chinese research communities and point to emerging research directions at the intersection of control theory, machine learning, and intelligent systems.

Keywords Model predictive control · Autonomous systems · Embodied intelligence

1 Introduction and background of model predictive control

Model predictive control (MPC), also known as Receding Horizon Control, has become a central paradigm in modern control engineering. Since its emergence in the late 1970s, MPC has evolved from an industry-driven heuristic into a formally grounded methodology that is widely adopted across high-value domains ranging from process industries and energy systems to robotics and intelligent transportation. Its appeal lies in its systematic use of predictive optimization to compute control inputs that satisfy performance objectives and respect system constraints over a moving time horizon.

In its most common form, MPC is implemented as a discrete-time, finite-horizon optimal control strategy, making it naturally suited to digital control and embedded computation. At each sampling instant, an optimization problem is solved to determine a sequence of future control actions that minimize a cost function subject to system dynamics, state and input constraints, and possibly terminal conditions. A major strength of MPC lies in its explicit treatment of constraints, setting it apart from classical linear controllers such as PID and LQR, which often require heuristic mechanisms for constraint enforcement [1]. After the optimal control sequence is determined, only the first control input is applied, and the procedure is repeated at the next sampling instant using updated state information. This receding-horizon approach imparts feedback properties to the controller, even though the optimization problem solved at each step is open-loop. The continual re-optimization enables MPC to adapt to disturbances, model uncertainties,

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and changing constraint activity in a predictive and responsive manner [2, 3].

The development of MPC can be broadly categorized along three interrelated dimensions: (i) its evolution from an industrial heuristic to a rigorous optimization-based control framework, underpinned by theoretical guarantees on stability, robustness, and performance [4]; (ii) the expansion into a rich family of algorithmic variants spanning linear, nonlinear, robust, stochastic, and adaptive formulations tailored to different system classes and uncertainty structures [5, 6]; and (iii) advances in computational and architectural technologies, including fast real-time solvers, hardware acceleration techniques, and distributed and cloud-based implementation paradigms, which have substantially improved MPC's applicability to time-critical and large-scale systems.

Along this trajectory, contributions from Chinese researchers (notably Yugeng Xi, who introduced predictive control to China in the late 1980s [7]) have played an important role in advancing both theoretical understanding and practical deployment. Notable contributions by Xi and his colleagues include elucidating the fundamental ingredients of MPC: predictive model, rolling optimization, and feedback correction [7], and formalizing a qualitative-synthesis perspective that integrates optimal control and Lyapunov arguments with terminal ingredients [8], particularly in the Chinese control community; advancing robust MPC formulations with rigorous stability and performance guarantees [9–12]; and promoting tractable deployment for large-scale and networked systems (e.g., urban transportation) through aggregation-based, distributed, and hierarchical algorithms [13–20]. Beyond these technical contributions, they have also shaped the field through flagship tutorial reviews and widely adopted textbooks [21–23], providing a coherent and accessible toolkit for MPC researchers and practitioners.

This article surveys the past, present, and future of MPC, with particular attention to foundational theory, modern applications (especially in the automotive domain), and emerging research directions. We also propose a forward-looking view of MPC as a general and principled framework for planning and control of embodied intelligent systems.

1.1 Motivation and scope

Originally developed to address the control challenges of petrochemical and process industries, MPC has evolved into a general-purpose framework with wide applicability. Its defining strengths include the ability to anticipate future behavior, enforce constraints in a principled way, and optimize multi-objective performance over a predictive horizon. With the development of fast solvers and embedded computing platforms, MPC has become viable for high-speed, safety-critical systems, including autonomous vehicles [24], aerospace systems [25], advanced robotics [26], smart grids [27], and so on.

This survey is structured around three overarching goals:

1. To trace the theoretical evolution of MPC from early industrial heuristics to a rigorous, optimization-based control framework, integrating key insights that have shaped its stability, robustness, and implementation in practice.
2. To review the widespread deployment of MPC across domains with particular emphasis on its adoption and advancement in automotive applications.
3. To explore future directions where MPC serves as a foundation for intelligent planning and control, particularly in the context of embodied intelligence.

We remark that the literature on MPC is vast and rapidly growing, making it infeasible to cover all relevant contributions in detail. In this article, we focus on representative works that illustrate key directions and flagship advances. For readers interested in a more comprehensive treatment of MPC theory, algorithms, and applications, we refer to the classic textbook by Rawlings, Mayne, and Diehl [3], as well as the monographs by Xi [22, 23] and Chen [28], which have played a foundational role in advancing MPC education and research in China. In addition, there already exist survey articles devoted to specialized topics such as robust MPC [29], stochastic MPC [30], distributed MPC [31], learning MPC [32], and others. Rather than attempting to review each of these directions in depth, our aim here is to provide an overarching perspective on the developmental trajectory of MPC, emphasizing the key milestones and thematic shifts that have shaped the field.

1.2 Core principles of MPC

At its core, MPC operates on the following receding-horizon loop:

1. *State measurement*: Measure (or estimate using an observer) the current system state x_t.
2. *Predictive optimization*: Solve the following problem for an optimal control input sequence $\{u_{k|t}\}_{k=0}^{N-1}$:

$$\min \sum_{k=0}^{N-1} \ell(x_{k|t}, u_{k|t}) + \ell_f(x_{N|t}) \tag{1a}$$

$$\text{s.t.} \quad x_{k+1|t} = f(x_{k|t}, u_{k|t}), \; k = 0, \ldots, N-1, \tag{1b}$$

$$x_{0|t} = x_t, \tag{1c}$$

$$x_{k|t} \in \mathcal{X}, \; u_{k|t} \in \mathcal{U}, \; k = 0, \ldots, N-1, \tag{1d}$$

$$x_{N|t} \in \mathcal{X}_f. \tag{1e}$$

3. *Execution*: Apply only the first input $u_t = u_{0|t}$ over a sampling interval.
4. *Receding horizon*: Repeat the process at the next timestep.

In (1), the notation $(\cdot)_{k|t}$ denotes the predicted value of a variable, either the system state x or control input u at future timestep $t + k$, based on information available at current time t. The parameter N specifies the length of the finite prediction horizon. The functions ℓ and ℓ_f represent stage cost and terminal cost, respectively. The sets $\mathcal{X}$, $\mathcal{U}$, and $\mathcal{X}_f$ define the admissible regions for the state, input, and terminal state (i.e., the state at the end of the prediction horizon). The function f represents a model used to predict the system dynamics over the horizon.

Key features The following characteristics underscore the power of MPC as a unifying control paradigm and its suitability for modern complex systems with stringent safety and performance requirements:

- *Predictive feedback*: Although each optimization is performed in an open-loop fashion, the receding-horizon structure (replanning at every timestep) yields closed-loop behavior capable of reacting to disturbances and model errors.
- *Multi-objective optimization*: The cost function can be flexibly designed to encode multiple performance objectives such as reference tracking, energy efficiency, control smoothness, and safety margins enabling systematic trade-off and prioritization.
- *Constraint handling*: MPC incorporates constraints on state and input variables explicitly within the optimization process, enabling formal compliance with physical limits and safety specifications.
- *Generality*: The predictive model f can take various forms, ranging from physics-based equations to data-driven models and neural networks. This flexibility makes MPC broadly applicable across diverse system classes and computational platforms.

1.3 Organization

The remainder of this article is organized as follows: Section 2 traces the historical evolution of MPC, highlighting key theoretical developments in stability, inherent robustness, and the emergence of major algorithmic variants. Section 3 examines the current state of MPC, focusing on real-time and scalable computation, data-driven approaches, and domain applications, with an emphasis on automotive systems. Section 4 envisions future directions for MPC as a foundational and general mechanism for planning, learning, and safety in embodied intelligent agents. Section 5 offers concluding remarks and synthesizes perspectives for the next generation of MPC research.

2 The past: theoretical foundations and evolution of MPC

MPC originated from industry-driven innovations in the 1970s and evolved into one of the most powerful frameworks in modern control engineering. Its development followed a clear trajectory: from heuristic algorithms to rigorous theoretical analysis, from industrial batch processes to safety-critical embedded systems. In this section, we review the key milestones in the early development of MPC, including the emergence of stability theory, the concept of inherent robustness, and various algorithmic variants that form the basis for MPC's modern capabilities. Chinese scholars particularly those active from the 1980s onward contributed substantially to this evolution, both in foundational research and in applied extensions.

2.1 Origins of MPC and foundational theoretical developments

MPC's roots lie in the process industry, where constrained multivariable control presented a long-standing challenge. Pioneering algorithms such as Model Algorithmic Control (MAC) and Dynamic Matrix Control (DMC) emerged in the 1970s to address this issue using output predictions and finite-horizon optimization [33, 34]. However, these early approaches lacked rigorous treatment of stability and robustness.

During the 1980s and 1990s, MPC became formalized through frameworks such as generalized predictive control (GPC) and other receding-horizon schemes, which introduced explicit handling of constraints and optimization-based feedback [2, 35]. These developments shifted MPC from an industrial heuristic to a control-theoretic discipline with provable properties.

In parallel, Chinese researchers began exploring predictive control frameworks. Notably, Yugeng Xi was among the first to introduce MPC theory in China. In the late 1980s, he proposed a multilayer intelligent predictive control architecture that integrated planning, feedback, and constraint handling, effectively anticipating the hierarchical and distributed MPC frameworks that would gain prominence decades later [7]. This work provided a conceptual bridge between industrial needs and emerging tools, laying the foundation for the subsequent widespread MPC research in China.

2.1.1 Stability theory of MPC

A central theoretical concern in MPC is the assurance of closed-loop stability under finite-horizon operation. Unlike infinite-horizon optimal control, which naturally yields stabilizing policies, MPC must incorporate certain structural elements such as terminal constraints or costs to guarantee that the closed-loop system remains stable over time [36].

One of the earliest rigorous stability results for general MPC formulations extending beyond linear regulators was provided in 1988 by Keerthi and Gilbert [37], who showed that optimal feedback laws for constrained nonlinear discrete-time systems can be approximated via moving-horizon strategies. Their work proved asymptotic stability of such strategies under mild assumptions, making it the first formal analysis of nonlinear MPC stability and laying foundational groundwork for later developments. Building on the growing interest in handling constraints in control systems, Gilbert and colleagues introduced the concepts of maximal output admissible sets in the late 1990s [38, 39]. These tools provided a set-theoretic approach to define feasible regions and to design invariant terminal sets, which remain essential to many modern MPC stability formulations.

In parallel, significant progress was made in China. During the 1990s, Yugeng Xi and colleagues investigated the closed-loop properties of GPC, producing a series of foundational results [40–42]. Addressing the challenge of tractable nonlinear MPC design without requiring exact terminal ingredients, Chen and Allgöwer introduced the quasi-infinite horizon MPC framework in 1998 [43]. By leveraging stage costs with appropriate decay properties, their formulation ensured asymptotic stability while avoiding the need for explicit terminal regions or costs, an advancement that significantly facilitated the practical application of nonlinear MPC, particularly in embedded and automotive systems.

In the seminal survey article [2], Mayne et al. synthesized many of these ideas into a general and now widely adopted framework for finite-horizon constrained MPC. Their approach formalized three sufficient ingredients for guaranteeing stability: (i) a terminal cost that approximates the infinite-horizon value function, (ii) a terminal constraint set that is invariant under a local stabilizing law, and (iii) a stage cost that acts as a Lyapunov function within the terminal region. This formulation is considered canonical in the field and underpins much of modern MPC theory and application. Systematic methods for constructing these ingredients for nonlinear systems include approximate dynamic programming to estimate stabilizing terminal costs [44]; Hamilton-Jacobi reachability and viability-kernel methods to compute controlled-invariant terminal sets [45, 46]; sum-of-squares-based semidefinite programs and occupation-measure-based convex relaxations to synthesize control-Lyapunov functions and invariant terminal regions [47, 48]; among other approaches [3].

Together, these contributions spanning moving-horizon approximation, set invariance, and terminal-relaxed design form the backbone of MPC stability theory. They continue to inform controller synthesis in both academic research and industrial practice, particularly as MPC extends to uncertain, distributed, and learning-enabled adaptive systems.

2.1.2 Inherent robustness of MPC

A critical insight in the MPC literature is that even when uncertainties are not explicitly modeled, MPC often exhibits a degree of *inherent robustness*. This robustness arises primarily from the receding-horizon mechanism: each optimization re-plans based on updated state measurements, allowing the controller to attenuate small disturbances before they propagate.

Early insights into this phenomenon were offered by Muske and Rawlings [49], who observed that nominal MPC controllers often exhibit stable behavior and maintain feasibility under small disturbances, even when such disturbances are not explicitly modeled in the formulation. Scokaert et al. [50] extended this understanding by establishing conditions under which nonlinear MPC remains stabilizing in the face of perturbations.

Pushing these insights further, researchers have developed a variety of analytical tools and formulations to quantify robustness margins and extend the permissible range of uncertainty [51–56]. Within the quasi-infinite horizon MPC framework proposed by Chen and Allgöwer [43], Yu et al. [57] provided a detailed analysis of the robustness properties of nonlinear MPC under bounded disturbances. They established conditions under which recursive feasibility and input-to-state stability are preserved. These results generalized earlier formulations and provided practical insights for implementing MPC in embedded systems operating under uncertainty.

Collectively, these contributions establish that MPC possesses a remarkable degree of robustness, even in its nominal form, due to its structure, especially its recursive nature. This has made MPC particularly attractive in safety-critical and uncertain environments where robustness is a central requirement.

2.2 Key MPC variants and their historical emergence

As MPC matured, several algorithmic variants emerged to address different classes of systems and uncertainty models. These developments have significantly shaped both theoretical research and practical applications.

2.2.1 Dynamic models in MPC: linear versus nonlinear formulations

Linear and explicit MPC The foundational form of MPC assumes linear system dynamics and quadratic cost functions, often referred to as *Linear-Quadratic MPC*. The controller solves a constrained finite-horizon optimal control problem of the form:

$$\min \sum_{k=0}^{N-1} \left(x_{k|t}^{\mathrm{T}} Q x_{k|t} + u_{k|t}^{\mathrm{T}} R u_{k|t} \right) + x_{N|t}^{\mathrm{T}} P x_{N|t} \tag{2a}$$

$$\text{s.t. } x_{k+1|t} = A x_{k|t} + B u_{k|t},\ k = 0, \ldots, N-1, \tag{2b}$$

$$x_{0|t} = x_t, \tag{2c}$$

$$x_{k|t} \in \mathcal{X} = \{x : Hx \leq h\},$$

$$u_{k|t} \in \mathcal{U} = \{u : Gu \leq g\},\ k = 0, \ldots, N-1, \tag{2d}$$

$$x_{N|t} \in \mathcal{X}_f = \{x : H_f x \leq h_f\}, \tag{2e}$$

where $Q \succeq 0$, $R \succ 0$, and $P \succeq 0$, which are frequently referred to as penalty matrices, specify the cost weights, the dynamics model is a linear model defined by the matrices A and B, and the admissible regions $\mathcal{X}, \mathcal{U}$, and $\mathcal{X}_f$ are convex polyhedral sets. This class of problems gives rise to convex Quadratic Programming (QP) formulations, which can be solved efficiently and reliably using standard optimization algorithms. Due to its practical relevance for tasks such as set-point regulation and reference tracking, as well as its computational tractability and the widespread availability of efficient QP solvers, linear MPC has become and remains the dominant formulation in industrial applications [58, 59].

Linear MPC has a long and well-established history of investigation. Over the years, its development has been grounded in several core mathematical foundations that continue to underpin its modern application. These include polyhedral invariance theory for constraint satisfaction and feasibility guarantees [39, 60], stability and robustness analysis [2], which ensures reliable long-term performance, duality theory for efficient online optimization, and parametric programming enabling offline computation and explicit control laws [1, 61]. Together, these tools provide a rigorous framework for certifying constraint satisfaction, stability, robustness, and scalability, making linear MPC a widely trusted solution for multivariable constrained control.

An important milestone was the development of explicit MPC [1, 61], which transforms the online optimization problem into an offline parametric programming problem. By partitioning the feasible state space into polyhedral regions, explicit MPC constructs a piecewise-affine control law of the form:

$$u_t = K_i x_t + c_i \ \text{ if } \ x_t \in \mathcal{R}_i, \tag{3}$$

where each region $\mathcal{R}_i$ corresponds to a polyhedral partition of the feasible set. During runtime, control input evaluation reduces to identifying the active region and applying the corresponding affine feedback, enabling real-time deployment on hardware with limited computational capability. This paradigm is especially advantageous in applications with stringent timing constraints, such as automotive ECUs, power converters, and embedded robotics.

Despite its apparent simplicity, linear MPC remains an active research area, especially in embedded and resource-constrained environments [62–65]. With the advent of lightweight solvers and automated code generation tools, such as CVXGEN [66] and qpOASES [67], the reach of linear MPC continues to expand into fast-sampling and safety-critical domains. The textbook by Borrelli, Bemporad, and Morari [68] provides a comprehensive treatment of linear and hybrid MPC theory and implementation, forming a widely adopted reference for both researchers and practitioners.

Nonlinear MPC Many engineering systems exhibit nonlinear behavior due to intrinsic physical laws, constraint-induced effects, and complex interactions between subsystems. In such scenarios, linear approximations often fall short, and accurate control requires predictive models that capture the system's nonlinear dynamics.

Nonlinear MPC extends the predictive control framework by solving, at each sampling step, a nonlinear optimization problem subject to dynamic and operational constraints [5]. This introduces several challenges, notably non-convexity, increased computational demands, and the difficulty of establishing recursive feasibility and stability guarantees.

To address these challenges, algorithmic advances such as multiple shooting [69], direct collocation [70], and Sequential Quadratic Programming (SQP) [71] laid the groundwork for practical implementations. The Real-Time Iteration (RTI) method [72–74] marked a significant step forward, enabling efficient online optimization by exploiting the problem's sequential structure. Modern software frameworks including ACADO [75], CasADi [76], and FORCESPRO have further facilitated nonlinear MPC deployment in embedded systems.

Despite its higher computational demands relative to linear MPC, nonlinear MPC provides a flexible and powerful framework for handling nonlinear dynamics and complex constraints. It remains an active and evolving area of research. While theoretical results on stability and robustness have been established under certain assumptions [2, 77], general-purpose guarantees are not yet comprehensive particularly for non-conventional problem formulations, systems with model uncertainties, and under limited state information [78]. Ongoing advances in numerical optimization, automated code generation, and hardware acceleration continue to enhance its real-time feasibility and broaden its applicability across safety-critical and high-performance domains.

It is worth noting that, while most MPC formulations are based on state-space models, Nonlinear AutoRegressive with eXogenous input (NARX) models are also widely used in industrial processes. NARX models capture nonlinear input-output dynamics and can be incorporated into predictive control schemes [79–81]. Moreover, a NARX model can be reformulated into a state-space representation by defining the regressor vector as a pseudo-state [82]. This transformation enables the application of conventional state-space MPC formulations, including constraint handling and stability analysis, while preserving the modeling advantages of NARX structures.

2.2.2 Uncertainty handling in MPC: robust, stochastic, and adaptive frameworks

Although nominal MPC exhibits a degree of inherent robustness due to its receding horizon implementation and feedback structure, such robustness is generally limited to small disturbances and model inaccuracies. For systems subject to significant uncertainty, either deterministic or probabilistic, ensuring constraint satisfaction and performance guarantees requires more principled formulations. This has led to the development of robust, stochastic, and adaptive MPC as complementary frameworks for uncertainty-aware control.

Robust MPC Robust MPC targets constraint satisfaction and performance guarantees under worst-case uncertainty, typically modeled as bounded disturbances or structured model mismatch [29]. A foundational approach is min-max optimization (i.e., min-max MPC), where the control sequence is optimized to perform well under the worst admissible disturbance realization [83–85]. This delivers strong, broadly applicable worst-case guarantees, but in general leads to non-convex and computationally demanding problems. Tractability improves by restricting the search to parametrized policies, at some loss of generality and with added conservatism. For instance, under linear dynamics and polytopic uncertainty, the min-max problem can be reformulated as a Linear Program (LP) by confining the controller to affine feedback policies [86].

For robust constraint satisfaction, an alternative strategy is constraint-tightening MPC. It enforces a nominal (disturbance-free) trajectory to satisfy robustly tightened constraints. The tightenings are pre-computed typically from bounds on disturbance-induced error so that the actual trajectory satisfies the original constraints for all admissible disturbances. Tube-based MPC makes this mechanism explicit by decomposing the dynamics into a nominal subsystem and an error subsystem, stabilizing the latter via an ancillary feedback controller, and thereby confining the actual trajectory to a bounded tube around the nominal. The tube then serves as an explicit robustness margin, allowing the nominal constraints to be robustly tightened according to the tube's cross-section or radius. In linear systems with bounded additive disturbances, this yields convex (often LP or QP) online problems with favorable scalability [87–90]; the trade-off is conservatism governed by the tube shape, which is dependent on the chosen stabilizing ancillary gain. The approach extends to output-feedback [91, 92] and to nonlinear settings [93–96], while computing tight tube and tightenings is more challenging in the nonlinear case. Another class of constraint-tightening MPC comprises robustness-constraint formulations, which impose explicit robustness constraints directly in the MPC optimization without introducing a tube-bounded error system [97, 98]. In these schemes, the nominal predictions are required to remain within a restricted admissible set defined by these added robustness constraints, to ensure that all disturbance-affected trajectories satisfy the original constraints.

Another robust strategy leverages Robust Control Invariant (RCI) sets [99–104]. By embedding RCI sets in the online optimization, these schemes ensure recursive feasibility and robustness guarantees without explicitly enumerating disturbance trajectories, shifting most of the computational burden offline to set construction. For linear and polynomial systems, RCI sets can be computed with Linear Matrix Inequalities (LMI)-based methods and semidefinite programs, but these methods can scale poorly with dimension, and coarse approximations increase conservatism.

Because robust MPC targets worst-case guarantees, it is inherently conservative, often at the expense of nominal performance. Balancing computational tractability with performance conservatism is a central theme in robust MPC research. When richer information about uncertainty is available, alternative frameworks may be leveraged to reduce conservatism and improve performance.

Stochastic MPC In contrast, stochastic MPC models uncertainty probabilistically and enforces constraints in a probabilistic sense [30]. It is especially relevant in systems where uncertainty is modeled from data or measurement noise and strict worst-case performance is unnecessarily conservative. By relaxing hard guarantees to chance guarantees, stochastic MPC enables more balanced performance Crisk trade-offs.

Core techniques in stochastic MPC include chance-constrained optimization, where constraints are required to hold with a specified probability [105–108]. Such formulations are often reformulated into tractable convex approximations, e.g., using Boole's inequality, constraint separation, or distributional assumptions. Scenario-based approaches approximate chance constraints by sampling uncertainty realizations and enforcing satisfaction over the sampled set [109–112], offering a nonparametric means of handling arbitrary distributions, though scalability depends on the required number of scenarios for statistical guarantees. Distributionally robust stochastic MPC further hedges against ambiguity in the underlying distribution by enforcing constraints for all distributions within an ambiguity set (e.g., defined by moments or Wasserstein balls) [113–115]. This yields robustness against model misspecification while preserving probabilistic flexibility.

Recent work integrates learning-based uncertainty quantification into stochastic MPC to improve adaptivity. Examples include Gaussian process-based MPC [116] and Bayesian distributionally robust formulations that update posterior-informed ambiguity sets [117]. These directions emphasize the synergy between data-driven learning of uncertainty and principled risk-aware decision-making in stochastic MPC.

Adaptive MPC Unlike robust or stochastic MPC which fix an uncertainty description a priori, adaptive MPC leverages online data to reduce uncertainty or adapt to changes over time, thereby improving closed-loop performance. It is particularly effective in systems with static or slowly time-varying uncertainty.

A common formulation is indirect adaptive MPC, which employs recursive estimation techniques to update predictive model parameters online and embeds these updates into the MPC optimization problem [118–121]. This approach preserves computational tractability but typically requires safeguards for stability and constraint satisfaction during transients. Direct adaptive MPC, in contrast, updates the controller law without explicit model identification, enabling faster adaptation but involving more challenging analysis [122, 123].

Adaptive MPC is closely related to modern data-driven and learning-based MPC, which extend the principle of online adaptation with richer data-driven models and closed-loop learning mechanisms. These approaches position adaptive MPC as a bridge between classical online identification and the broad family of data-driven control methods.

While nominal MPC offers some robustness by virtue of its feedback nature, robust, stochastic, and adaptive MPC extend this capability in formal and complementary ways. Robust MPC prioritizes worst-case guarantees, stochastic MPC manages uncertainty through probabilistic trade-offs, and adaptive MPC leverages online data to reduce uncertainty. Together, they represent three essential pillars of predictive control under uncertainty.

The theoretical foundations of MPC particularly around stability, robustness, and algorithmic variants have matured into a robust and widely applicable framework. The field developed through contributions across continents, and Chinese researchers have been integral in this journey. From the early theoretical contributions of Yugeng Xi, who helped introduce predictive control to China and shaped its foundational landscape, to ongoing research in robustness, nonlinear systems, and large-scale industrial deployment, the development of MPC reflects a globally intertwined scientific evolution. In the next section, we examine how these foundations have enabled the widespread application and technological integration of MPC in the modern data-driven, embedded systems era.

3 The present: computational advances and widespread deployment of MPC

In the present stage, MPC is marked by rapid computational advances and increasingly widespread deployment, with progress spanning real-time and distributed implementations, the integration of data-driven methods, and large-scale adoption in domains such as automotive systems.

3.1 Real-time and distributed computational advances for MPC

As MPC continues to expand beyond its roots in process industries into domains characterized by fast and safety-critical dynamics such as automotive systems, robotics, and aerospace, the demand for real-time, reliable computation has become increasingly critical. In modern embedded applications, control decisions must often be made within strict timing constraints, frequently on the order of milliseconds or less. At the same time, the rise of large-scale and interconnected systems particularly multi-agent networks, cyber-physical infrastructures, and cloud/edge computing architectures has introduced new computational and architectural challenges. These emerging system architectures call for MPC implementations that are not only fast but also scalable and decentralized by design.

To address these evolving demands, two complementary computational strategies have gained prominence. First, advances in fast optimization algorithms and hardware acceleration have significantly enhanced the feasibility of implementing MPC in embedded platforms with tight computational budgets. These developments are particularly vital for real-time control in high-speed and resource-constrained applications. Second, the emergence of distributed and cloud-based MPC frameworks has enabled scalable coordination in spatially distributed and functionally heterogeneous systems. Here, we discuss distributed MPC primarily from a viewpoint of architecting and spatially decomposing the overall computations for solving the system-level MPC problem, rather than emphasizing its algorithmic variant features. From this perspective, both real-time optimization and distributed implementation represent complementary advances in computational paradigms, and it is reasonable to group them together in this section to highlight their shared role in enabling practical and scalable MPC deployment. While distributed MPC is undoubtedly also shaped by factors such as spatially distributed sensing and actuation, communication, and privacy at the edge, the core consideration in determining centralized versus distributed MPC often remains the organization of computation.

Real-time optimization Real-time implementation remains one of the most active and impactful frontiers in MPC research. The requirement to solve constrained optimization problems online at every control step necessitates fast, reliable, and resource-aware solvers. This is especially critical in domains such as automotive, robotics, and aerospace, where sampling rates are on the order of milliseconds or less.

The development of efficient optimization algorithms has been foundational. Primal-dual interior-point methods [124] and active-set strategies have matured into embedded-ready solvers such as CVXGEN [66], qpOASES [67], and OSQP [125]. They focus on different algorithmic strategies: CVXGEN generates highly problem-specific, library-free C code with minimal overhead, qpOASES exploits warm-starting to accelerate solution of related QPs, while OSQP leverages operator splitting for robustness and scalability. Collectively, these solvers provide fast and predictable solutions, especially for linear-quadratic MPC, in embedded applications. For nonlinear MPC, the RTI scheme proposed by Diehl et al. [72, 73] marked a conceptual shift: exploiting the strong similarity between successive MPC problems as the horizon advances, it performs only a single SQP iteration per sampling step instead of solving each optimization to full convergence, while still ensuring local convergence and closed-loop stability under mild assumptions. Building on the same principle, Time-Distributed Optimization (TDO) proposed by Liao-McPherson et al. [126, 127] reformulates MPC as a rolling optimization process and dynamically allocates iterations across timesteps to reduce per-step load. Compared to RTI, TDO further increases flexibility by distributing effort over time, making it particularly suitable for embedded systems where the resources available for MPC may vary, for instance, depending on the real-time demands of perception or other concurrent modules. In a complementary direction, Hong et al. [128] introduced a mechanism knowledge-enhanced, timescale graph-parallel computation method for fast MPC implementation, reporting significant speedups relative to baseline methods.

Beyond algorithmic advances, hardware acceleration has become essential for achieving low-latency execution. Xu and Guo demonstrated the feasibility of implementing nonlinear MPC on FPGAs by exploiting pipeline scheduling and parallelism to meet sub-millisecond deadlines in embedded platforms [129–131]. Yu et al. [132] and Bishop et al. [133] leveraged GPU architectures for high-throughput linear MPC by accelerating QP solvers through massive parallelism. Complementing these efforts, Khusainov et al. [134] proposed a codesign methodology that jointly optimizes the MPC algorithm and computing hardware, enabling an optimal performance-resource trade-off. These hardware-based techniques can be combined with algorithmic advances, yielding integrated solutions that advance the practical frontier of real-time MPC.

Distributed and cloud MPC As MPC expands into large-scale and networked environments, Distributed MPC (DMPC) has become a compelling framework for coordinating control across multiple interacting subsystems. DMPC typically decentralizes the global optimization by assigning local subproblems to individual agents, each with partial system views and local objectives, while coordinating through communication to ensure cohesive system-level performance. This structure is particularly well suited for multi-agent systems such as vehicle platooning [135, 136], smart grids [137, 138], and building automation [139, 140], where centralized control becomes impractical due to scalability, privacy, or communication limitations.

Foundational theoretical efforts have laid the groundwork for DMPC design. Scattolini [141] and Christofides et al. [31] introduced a widely adopted taxonomy of DMPC architectures, classifying coordination schemes by their cooperative versus non-cooperative/independent objectives, global versus local communication, and synchronous versus asynchronous update structures. These distinctions frame the trade-offs between communication burden, convergence guarantees, and implementation feasibility. In linear systems, distributed constraint handling and performance coordination have been addressed through consensus-based schemes [142] and dual decomposition methods [143]. Recent advances have pushed DMPC toward improved scalability and efficiency. Zhou and Li [144] proposed a DMPC framework based on neighbor screening, which dynamically adjusts the communication topology based on agent proximity and relevance, reducing bandwidth demands without sacrificing system performance. Complementing previous efforts, Shorinwa and Schwager [145] proposed a separable-optimization DMPC method, in which each agent communicates only with relevant neighbors and solves a reduced local MPC subproblem. The method achieves linear convergence in convex settings, significantly enhancing scalability and preserving privacy in large-scale multi-agent systems. Building on this trajectory, Zhou et al. [17] and Ma et al. [18] introduced event-triggered distributed MPC schemes for nonlinear and piecewise-affine systems, enabling communication and computation to occur only when necessary while guaranteeing recursive feasibility and closed-loop stability.

An important extension of DMPC in recent years is the emergence of cloud-based MPC, enabled by rapid advances in cloud computing, edge intelligence, and networked communication infrastructure. In modern cyber-physical systems such as smart buildings, energy networks, and industrial automation computational demands and large-scale coordination requirements increasingly motivate the offloading of optimization tasks to cloud platforms. Cloud-based MPC frameworks leverage centralized or distributed cloud resources to perform high-fidelity and long-horizon planning, global coordination, and data-driven adaptation, while interfacing with local controllers that handle real-time actuation. This paradigm enables scalable, computation-intensive control strategies that are otherwise infeasible on embedded hardware. Skarin et al. [146, 147] proposed a cloud MPC framework that maintains performance despite network-induced delays by adapting horizon lengths and fallback strategies. Li et al. [148] introduced a cloud-based MPC scheme using parallel multi-block ADMM to handle large-scale problems efficiently. Li et al. [149] and Ma et al. [150] proposed cloud-edge cooperative MPC designs that integrate high-fidelity optimization in the cloud with simplified local MPC controllers to ensure robust performance and constraint satisfaction. Despite its promise, cloud-based MPC poses several active research challenges including managing asynchronous updates, coping with communication latency and packet loss, enforcing real-time constraints under cloud execution, and preserving data privacy in networked environments. These issues have spurred a wave of recent research aimed at enhancing the theoretical and practical viability of cloud-based MPC frameworks [151–153].

Advances in fast optimization algorithms, embedded hardware acceleration, and distributed computing frameworks have broadened the applicability of MPC to engineering systems characterized by stringent timing constraints and decentralized structure. These innovations underscore the field s shift from theoretical control design to high-performance, scalable deployment across diverse application domains.

3.2 MPC in the data-driven era

The modern control landscape is increasingly shaped by the abundance of data. In many domains such as autonomous driving, robotics, building energy management, and smart grids, data from sensors, logs, and simulations is readily available, while accurate first-principles models have become progressively harder to obtain due to growing system complexity, pronounced nonlinearities, and the presence of unmodeled dynamics. Meanwhile, advances in machine learning have enabled the extraction of rich and essential dynamical information from raw data. These developments have motivated renewed interest in *Data-Driven MPC* methods, so named for their extensive use of data throughout the control design process. Broadly, data-driven MPC approaches can be categorized into two types: *direct* and *indirect*.

Direct data-driven MPC Direct data-driven MPC methods bypass the intermediate step of model identification and use measured system trajectories to predict future behavior and compute control actions. One representative approach is the *Data-enabled Predictive Control (DeePC)* method, introduced by Coulson et al. [154]. DeePC uses Hankel matrices built from measured input-output trajectories to formulate the prediction and optimization problem directly. This method is rooted in the behavioral systems theory [155], particularly, Willems' Fundamental Lemma [156], which asserts that any trajectory of a controllable linear system can be expressed as a linear combination of past measured trajectories, provided persistency of excitation is met. Theoretical characterizations of DeePC and its extensions to noisy and nonlinear systems continue to be active areas of investigation [157–160]. Yang et al. [161–163] developed a data-driven technique integrated into a robust MPC architecture for unknown-but-bounded time-independent or slowly time-varying linear systems. The method guarantees recursive feasibility and input-to-state stability under noisy input-state data and parametric model uncertainty. Li et al. [164] contributed an alternative direct data-driven MPC method. This method ensures stability and H_∞-type disturbance attenuation while satisfying time-domain constraints, by solving LMI-type online optimization problems.

Indirect data-driven MPC In contrast, indirect approaches first learn a structured model or estimate its parameters from data using system identification, regression, or embedding techniques and then use this model in a standard MPC framework. While not a new concept (system identification has a long and rich history [165]), the data-driven era has brought renewed attention and innovation to this direction.

An increasingly prominent method is *Koopman MPC*, which leverages the Koopman operator theory to approximate nonlinear dynamics through a lifted linear representation in a higher-dimensional observable space [166]. In this framework, data is used to identify the lifted dynamics typically via methods such as Extended Dynamic Mode Decomposition (EDMD) or neural network-based lifting lifting, enabling the use of linear MPC techniques for systems with nonlinear behavior. Koopman MPC provides a compelling trade-off between model expressiveness and computational tractability, particularly for systems exhibiting structured nonlinearities [167, 168]. The framework has been extended to incorporate robustness guarantees and safety-critical considerations in embedded applications [95, 169, 170].

A related and rapidly expanding direction within indirect data-driven MPC is the use of neural networks and other machine learning models to enhance various components of the control architecture. A common approach involves training a neural network from input Coutput data to approximate system dynamics, which is then embedded in the MPC formulation for trajectory prediction [171, 172]. This strategy leverages the universal function approximation properties of deep networks, making it particularly appealing for complex nonlinear systems that defy analytical modeling [173, 174]. Beyond dynamics modeling, recent works have employed machine learning particularly Reinforcement Learning (RL) to tune MPC elements, such as cost weights, horizon length, and constraint parameters [175–182]. Such RL-based tuning can mitigate suboptimality arising from model mismatch, finite-horizon truncation relative to the infinite-horizon optimum, and imperfect terminal ingredients. This broad class of methods is collectively referred to as *Learning-Based MPC* [32], encompassing both supervised learning for model construction or online update and RL for adaptive performance shaping. Notable works in this space include [183–188]. These methods hold strong promise for improving adaptability and performance in uncertain or high-dimensional environments, but they also raise challenges related to generalization and certifiable safety, particularly with respect to feasibility and stability. A growing body of work addresses these issues by incorporating robust control techniques such as constraint tightening, input-to-state stability analysis, and Lyapunov-based safety filtering, aimed at providing formal guarantees while preserving the flexibility of data-driven methods [189–192].

Together, these data-driven MPC approaches are emblematic of a broader shift toward *Learning-Based Control*. By systematically integrating data into the control design loop, either through direct optimization or model learning, they offer new avenues for deploying MPC in complex, uncertain, and high-dimensional environments where conventional modeling is infeasible or insufficient.

3.3 Broad deployment of MPC and automotive focus

3.3.1 Broad deployment of MPC

Over the past four decades, MPC has evolved far beyond its origins in the process industries to become a foundational paradigm for multivariable, multi-objective, and safety-critical control across a wide array of domains including aerospace [25], robotics [26, 193], energy systems [27, 194], and transportation [24].

In aerospace, MPC has enabled robust trajectory planning and tracking under uncertainty for both space and aerial vehicles [195, 196]. In robotics, MPC is extensively used for motion planning, adaptive locomotion, and interaction-aware control in both wheeled and humanoid platforms [197–200], benefiting from its predictive capabilities and real-time constraint enforcement.

In networked energy and transportation systems, MPC has proven particularly effective for coordinating large-scale, distributed infrastructures. Yugeng Xi and collaborators have made substantial contributions in this domain through the development of scalable MPC schemes for such systems. For example, Lin et al. [201, 202] developed computationally-efficient MPC algorithms for urban traffic networks by reformulating nonlinear problems into tractable forms and employing model simplification techniques, demonstrating real-time feasibility in traffic signal optimization. Building on this, Ling et al. [19] and Zhou et al. [20] proposed hierarchical MPC architectures that partition urban traffic networks into manageable subsystems and coordinate their behavior through layered control, enhancing scalability and modularity. More recently, Wu et al. [16] designed a distributed, event-triggered MPC approach for urban traffic light control, which reduces communication and computation overhead by activating control updates only when required, offering a viable solution for bandwidth-limited, city-scale deployments.

These developments collectively illustrate how MPC supported by advances in solver technology, distributed computation, and data-driven modeling has become a central tool for intelligent control in complex, uncertain, and interconnected systems.

3.3.2 MPC in automotive systems

Automotive applications represent one of the most active and industrially mature domains for MPC. Since the early 2010s, MPC has become a central component in numerous production-level and experimental vehicle control systems, driven by its ability to handle multivariable dynamics, physical constraints, and multi-objective formulations. This section reviews three major threads of MPC applications in automotive systems: energy-efficient driving, trajectory planning and tracking, and chassis control.

Energy-efficient driving and powertrain management MPC has become a key enabler of energy-efficient driving strategies, particularly for hybrid and electric vehicles (HEVs/EVs), for reducing fuel consumption and extending range. Thanks to its predictive optimization structure, MPC can naturally incorporate road grade, traffic flow, and signal timing into its lookahead horizon, enabling anticipatory control decisions that balance energy consumption and vehicle performance [203].

In powertrain energy management of HEVs/EVs, MPC is employed to dynamically allocate power between electric motors, internal combustion engines, and energy storage systems. By optimizing the power split in real time, MPC minimizes fuel consumption and emissions while meeting driver demands and respecting system constraints. Several notable works have demonstrated implementable MPC strategies that achieve energy efficiency and drivability improvement under real-time computational limits [204–206].

Another important line of work focuses on MPC for eco-driving and vehicle platooning. Eco-driving refers to the regulation of vehicle speed and acceleration to minimize energy consumption. MPC-based eco-driving strategies that incorporate preview information of preceding vehicle speed, road grade, and traffic signal timing have been proposed in [207–212]. Recent studies have also taken into account interactions with surrounding traffic participants [213]. Vehicle platooning and Cooperative Adaptive Cruise Control (CACC) are also effective methods for improving energy efficiency by reducing aerodynamic drag, enhancing traffic flow stability, and enabling cooperative behavior among vehicles. MPC-based vehicle platoon control and CACC strategies have been developed in [136, 214–218], incorporating inter-vehicle distance constraints, variable communication topologies, and robustness against external disturbances. These developments demonstrate the suitability of MPC for enabling energy-efficient, safe, and coordinated operation of road vehicles.

Trajectory planning and collision avoidance Trajectory planning for automated driving and Advanced Driver-Assis tance Systems (ADAS) is another key domain where MPC has demonstrated strong effectiveness. Its predictive optimization structure, together with its ability to explicitly enforce physical, safety, and comfort constraints, makes MPC particularly well-suited for generating feasible and reliable trajectories in dynamic environments. The literature on MPC-based trajectory planning is rich and diverse. Notable contributions include the MPC-based path planning framework developed by Liu et al. [219], the stochastic MPC approaches for lane change decision-making accounting for surrounding vehicle behavior uncertainties proposed by Suh et al. [220] and Brüdigam et al. [221], the interaction-aware trajectory prediction and planning framework based on integration of game theory and MPC presented by Liu et al. [222], and the unified planning approach based on a convex stochastic MPC formulation developed by Nair et al. [223].

In addition to trajectory planning, MPC has been extensively employed for trajectory tracking (including integrated planning and tracking) and real-time collision avoidance [224–232]. Its flexibility in incorporating vehicle dynamics, environmental constraints, and multi-dimensional performance objectives makes MPC a powerful and versatile tool for collision-aware trajectory tracking in both structured and unstructured environments.

Chassis control: Steering, suspension, and beyond MPC has a long-standing history in vehicle chassis control, with early applications tracing back to to the mid-1990s [233]. Its suitability for handling multivariable systems with physical and safety constraints made it an early candidate for chassis subsystems such as steering, braking, and suspension. In steering control, MPC has been widely applied to active steering, enabling enhanced stability and precise trajectory tracking in critical maneuvers [234–237]. In suspension systems, MPC optimizes damping or control force based on road preview and vehicle body dynamics to improve handling and ride comfort [233, 238–241]. Recently, this has evolved into integrated chassis control, where MPC coordinates multiple actuators spanning steering, braking, and suspension within a unified framework [242, 243]. These developments underscore MPC's sustained relevance in chassis control, from traditional safety systems to modern intelligent vehicle platforms.

The automotive sector continues to expand the frontiers of MPC deployment across electric powertrains, automated driving, and intelligent chassis systems. Looking ahead, the future of automotive MPC lies in deeper integration with perception, machine learning, and cloud connectivity while retaining its core strengths in multi-objective optimization, constraint handling, and formal performance guarantees.

4 The future: toward a unified embodied intelligence framework

MPC has progressed from an industry-inspired heuristic into a control framework with rigorous theoretical guarantees and broad impact across engineering domains. As it continues to advance, MPC is becoming increasingly interwoven with emerging computational paradigms, data-driven modeling, and learning-enabled adaptation, placing it at the frontier of intelligent decision-making. We envision a future in which ongoing research will not only continue to tackle long-standing challenges for MPC including extending guarantees to more general nonlinear settings, further improving real-time and scalable deployment, and enabling seamless online learning but also push the framework beyond its traditional boundaries, positioning it as a cornerstone of the embodied AI era.

4.1 MPC as a general principle for intelligent agents

MPC embodies a fundamental operational principle well-suited for intelligent agents, unifying measurement, prediction, optimization-based planning, execution, and continuous updating over a receding horizon. The core MPC paradigm, as outlined in Sect. 1.2, constitutes a powerful and generalizable feedforward and feedback structure.

A defining strength of MPC lies in its inherent flexibility regarding the prediction model. The predictive model can range from physics-based equations to purely data-driven neural networks or hybrid models integrating both physics and machine learning components. This flexibility allows MPC to function robustly across a variety of computational platforms and operational domains, from resource-limited embedded systems to distributed cloud-edge infrastructures. As a result, MPC naturally accommodates evolving computational architectures and system complexity.

The explicit capability of MPC to enforce constraints further enhances its role as a trustworthy decision-making mechanism, particularly in safety-critical and high-stakes scenarios. Constraint handling ensures safety compliance and performance guarantees, which are increasingly vital as intelligent agents operate autonomously in dynamic and uncertain environments.

Moreover, MPC extends significantly beyond classical control paradigms, encapsulating broader decision-making and planning contexts traditionally studied in computer science and artificial intelligence. Recent research demonstrates how MPC can be effectively utilized in Markov Decision Processes (MDP) [244–247] and decision-making within belief spaces [248–250], facilitating robust decisions under uncertainty and partial observability. In robotics, repeated online re-planning using methods such as Rapidly-exploring Random Trees (RRT), physics-informed RRT variants [251], and other sampling- or search-based algorithms where locally feasible trajectories are iteratively generated based on updated state and constraint information can be interpreted as specialized instances of the MPC paradigm.

Consequently, it is safe to envision that MPC, or closely related predictive and optimization-based strategies, will increasingly shape the future landscape of intelligent systems, particularly embodied intelligent agents. As these agents grow more sophisticated, integrating perception, cognition, and dynamic interaction with their environments, the general principle encapsulated by MPC provides a structured, reliable, and computationally scalable framework that naturally accommodates complexity and uncertainty.

4.2 MPC with learned world models

Models that describe how an environment evolves in response to an agent's actions, popularly referred to as *World Models* in recent AI literature, are increasingly regarded as foundational components of embodied intelligence. Prominent examples such as Dreamer [252, 253] and MuZero [254] demonstrate how learned world models enable agents to simulate and evaluate future trajectories internally. These models, typically implemented as neural networks and trained via supervised or reinforcement learning [255, 256], have been integrated with MPC in recent research [257, 258] to generate objective-driven behavior. This integration allows an intelligent agent to operate effectively in complex and uncertain environments by leveraging MPC's core strengths: recursive prediction, constraint enforcement, and closed-loop optimization. A notable instantiation of this principle is Meta's Joint Embedding Predictive Architecture (JEPA) [259], which unifies perception, prediction, and action through learned predictive embeddings.

For scalable deployment across diverse tasks, world models should adapt their level of abstraction according to task requirements. Coarse-grained models may suffice for high-level navigation or strategic planning, while fine-grained models are essential for precise low-level manipulation. This notion of task-adaptive granularity is critical for efficient and flexible integration within MPC frameworks [260].

MPC or planning frameworks analogous in spirit built upon learned world models have been successfully applied to visual navigation [261], robotic manipulation [262], and game-playing [254], demonstrating impressive generalizability and adaptability. These developments underscore the growing potential of unifying learning and predictive control to support intelligent, feedback-driven behavior in dynamic and uncertain environments.

4.3 Formal guarantees in AI planning and decision-making

As autonomous agents are increasingly deployed in safety-critical domains such as autonomous driving, robotics, and industrial automation, ensuring reliable and verifiable operation becomes more important, but also more challenging, especially due to the growing adoption of data-driven, neural, and generative AI methods. Techniques such as Large Language Models (LLMs), diffusion models, and Vision-Language-Action (VLA) systems enable complex multi-modal reasoning, but they often lack built-in mechanisms for handling physical constraints, real-time dynamics, or providing formal guarantees of safety and correctness.

A promising strategy to address this gap is the integration of MPC principles particularly its receding-horizon optimization structure and explicit constraint handling into modern AI planning architectures. This integration has gained significant traction in *Safe Reinforcement Learning*, where MPC-style mechanisms are used as safety filter or backup controller to ensure constraint satisfaction during exploration [263–268]. Recent efforts have also proposed hybrid frameworks in which high-level plans generated by generative models are verified or refined by MPC modules operating over known or learned dynamics [269, 270]. In such architectures, MPC acts as a trust layer, ensuring that behavior remains feasible and safe even when upstream reasoning is approximate or uncertain. Moreover, the structure of MPC particularly its ability to incorporate predictive models and reason under constraints offers a template for embedding formal verification techniques into AI planning.

As embodied AI systems continue to expand into open-world, safety-critical settings, the demand for planning and decision-making frameworks with formal safety and performance guarantees will continue to intensify. MPC, with its principled structure and rigorous theoretical foundations, is uniquely positioned to bridge the gap between flexible, high-level intelligence and grounded, reliable execution in embodied AI.

5 Conclusions

Over the past four decades, MPC has evolved from a process control heuristic into a rigorous and widely adopted framework for multivariable, multi-objective, and constrained control. Recent advances in fast solvers, embedded computing, distributed architectures, and data-enabled techniques have facilitated its broad deployment across domains such as robotics, transportation, and beyond.

Looking ahead, MPC is well-positioned to serve as a unifying paradigm for intelligent decision-making and control. Its capacity to integrate prediction, learning, and constraint enforcement makes it particularly suited for trustworthy embodied agents operating in complex, uncertain environments. Emerging challenges and opportunities including scalable implementation, integration with learned models, and formal guarantees under data-driven uncertainty will continue to shape the future of MPC and its role in next-generation autonomous systems.

References

1. Bemporad, A., Morari, M., Dua, V., & Pistikopoulos, E. N. (2002). The explicit linear quadratic regulator for constrained systems. *Automatica, 38*(1), 3–20.
2. Mayne, D. Q., Rawlings, J. B., Rao, C. V., & Scokaert, P. O. (2000). Constrained model predictive control: Stability and optimality. *Automatica, 36*(6), 789–814.
3. Rawlings, J. B., Mayne, D. Q., & Diehl, M. M. (2020). *Model predictive control: Theory, computation, and design* (2nd ed.). Nob Hill Publishing.
4. Garcia, C. E., Prett, D. M., & Morari, M. (1989). Model predictive control: Theory and practice—A survey. *Automatica, 25*(3), 335–348.
5. Grüne, L., & Pannek, J. (2017). *Nonlinear model predictive control: Theory and algorithms*. Springer.
6. Kouvaritakis, B., & Cannon, M. (2016). *Model predictive control: Classical, robust and stochastic*. Springer.
7. Xi, Y., Xu, X., & Zhang, Z. (1989). The status of predictive control and the multilayer intelligent predictive control. *Control Theory & Applications,6*(2), 1–7.
8. Xi, Y.-G., & Li, D.-W. (2008). Fundamental philosophy and status of qualitative synthesis of model predictive control. *Acta Automatica Sinica, 34*(10), 1225–1234.
9. Ding, B., Xi, Y., Cychowski, M. T., & O'Mahony, T. (2007). Improving off-line approach to robust MPC based-on nominal performance cost. *Automatica, 43*(1), 158–163.
10. De-Wei, L., & Yu-Geng, X. (2009). Design of robust model predictive control based on multi-step control set. *Acta Automatica Sinica, 35*(4), 433–437.
11. Li, D., & Xi, Y. (2010). The feedback robust MPC for LPV systems with bounded rates of parameter changes. *IEEE Transactions on Automatic Control, 55*(2), 503–507.
12. Huang, H., Li, D., Lin, Z., & Xi, Y. (2011). An improved robust model predictive control design in the presence of actuator saturation. *Automatica, 47*(4), 861–864.
13. Li, D., & Xi, Y. (2009). Quality guaranteed aggregation based model predictive control and stability analysis. *Science in China Series F: Information Sciences, 52*(7), 1145–1156.
14. Li, D., Xi, Y., & Lin, Z. (2013). An improved design of aggregation-based model predictive control. *Systems & Control Letters, 62*(11), 1082–1089.
15. Du, X., Xi, Y.,& Li, S. (2001) Distributed model predictive control for large-scale systems. In *Proceedings of the 2001 American control conference* (Vol. 4, pp. 3142–3143).
16. Wu, N., Li, D., Xi, Y., & Schutter, B. (2021). Distributed event-triggered model predictive control for urban traffic lights. *IEEE Transactions on Intelligent Transportation Systems, 22*(8), 4975–4985.
17. Zhou, Y., Li, D., Xi, Y., & Gao, F. (2022). Event-triggered distributed robust model predictive control for a class of nonlinear interconnected systems. *Automatica, 136*, Article 110039.
18. Ma, A., Li, D., & Xi, Y. (2025). Event-triggered distributed model predictive control for PWA systems. *International Journal of Robust and Nonlinear Control, 35*(2), 435–451.
19. Ling, T., Lin, S., & Xi, Y. (2013). Multi-level model-based control for large scale urban traffic networks. *IFAC Proceedings Volumes, 46*(13), 484–489.
20. Zhou, Z., De Schutter, B., Lin, S., & Xi, Y. (2017). Two-level hierarchical model-based predictive control for large-scale urban traffic networks. *IEEE Transactions on Control Systems Technology, 25*(2), 496–508.
21. Xi, Y.-G., Li, D.-W., & Lin, S. (2013). Model predictive control—Status and challenges. *Acta Automatica Sinica, 39*(3), 222–236.
22. Xi, Y. (2013). *Predictive control* (2nd ed.). National Defense Industry Press.
23. Xi, Y., & Li, D. (2019). *Predictive control: Fundamentals and developments*. Wiley.
24. Yu, S., Hirche, M., Huang, Y., Chen, H., & Allgöwer, F. (2021). Model predictive control for autonomous ground vehicles: A review. *Autonomous Intelligent Systems, 1*(4), 1–17.
25. Eren, U., Prach, A., Koçer, B. B., Raković, S. V., Kayacan, E., & Açıkmeşe, B. (2017). Model predictive control in aerospace systems: Current state and opportunities. *Journal of Guidance, Control, and Dynamics, 40*(7), 1541–1566.
26. Katayama, S., Murooka, M., & Tazaki, Y. (2023). Model predictive control of legged and humanoid robots: Models and algorithms. *Advanced Robotics, 37*(5), 298–315.
27. Hu, J., Shan, Y., Guerrero, J. M., Ioinovici, A., Chan, K. W., & Rodriguez, J. (2021). Model predictive control of microgrids—An overview. *Renewable and Sustainable Energy Reviews, 136*, Article 110422.
28. Chen, H. (2013). *Model predictive control*. Science Press.

29. Bemporad, A., & Morari, M. (1999). Robust model predictive control: A survey. In A. Garulli & A. Tesi (Eds.), *Robustness in identification and control* (pp. 207–226). Springer.
30. Mesbah, A. (2016). Stochastic model predictive control: An overview and perspectives for future research. *IEEE Control Systems Magazine, 36*(6), 30–44.
31. Christofides, P. D., Scattolini, R., de la Peña, M., & Liu, J. (2013). Distributed model predictive control: A tutorial review and future research directions. *Computers & Chemical Engineering, 51*, 21–41.
32. Hewing, L., Wabersich, K. P., Menner, M., & Zeilinger, M. N. (2020). Learning-based model predictive control: Toward safe learning in control. *Annual Review of Control, Robotics, and Autonomous Systems, 3*, 269–296.
33. Richalet, J., Rault, A., Testud, J. L., & Papon, J. (1978). Model predictive heuristic control: Applications to industrial processes. *Automatica, 14*(5), 413–428.
34. Cutler, C. R.,& Ramaker, B. L. (1980). Dynamic matrix control—A computer control algorithm. In *Proceedings of the 86th National Meeting of the American Institute of Chemical Engineers (AIChE)*, Houston, TX.
35. Clarke, D. W., Mohtadi, C., & Tuffs, P. S. (1987). Generalized predictive control—Parts I and II. *Automatica, 23*(2), 137–160.
36. Bitmead, R. R., Gevers, M., & Wertz, V. (1990). *Adaptive optimal control: The thinking man's GPC*. Prentice Hall.
37. Keerthi, S. S., & Gilbert, E. G. (1988). Optimal infinite-horizon feedback laws for a general class of constrained discrete-time systems: Stability and moving-horizon approximations. *Journal of Optimization Theory and Applications, 57*(2), 265–293.
38. Kolmanovsky, I., & Gilbert, E. G. (1998). Theory and computation of disturbance invariant sets for discrete-time linear systems. *Mathematical Problems in Engineering, 4*(4), 317–367.
39. Gilbert, E. G., & Tan, K. T. (2002). Linear systems with state and control constraints: The theory and application of maximal output admissible sets. *IEEE Transactions on Automatic Control, 36*(9), 1008–1020.
40. Xi, Y., & Li, J. (1991). Closed-loop analysis of the generalized predictive control systems. *Control Theory & Applications, 8*(4), 419–424.
41. Xi, Y., & Zhang, J. (1997). Study on the closed-loop properties of GPC. *Science in China Series E: Technological Sciences, 40*(1), 54–63.
42. Zhang, J., & Xi, Y. (1998). Several stability results on GPC system. *Control Theory & Applications, 15*(1), 24–30.
43. Chen, H., & Allgöwer, F. (1998). A quasi-infinite horizon nonlinear model predictive control scheme with guaranteed stability. *Automatica, 34*(10), 1205–1217.
44. Bertsekas, D. P., & Tsitsiklis, J. N. (1996). *Neuro-dynamic Programming*. Athena Scientific.
45. Mitchell, I. M., Bayen, A. M., & Tomlin, C. J. (2005). A time-dependent Hamilton-Jacobi formulation of reachable sets for continuous dynamic games. *IEEE Transactions on Automatic Control, 50*(7), 947–957.
46. Aubin, J.-P., Bayen, A. M., & Saint-Pierre, P. (2011). *Viability theory: New directions*. Springer.
47. Parrilo, P. A. (2000). Structured semidefinite programs and semi-algebraic geometry methods in robustness and optimization. PhD thesis, California Institute of Technology.
48. Korda, M., Henrion, D., & Jones, C. N. (2014). Convex computation of the maximum controlled invariant set for polynomial control systems. *SIAM Journal on Control and Optimization, 52*(5), 2944–2969.
49. Muske, K. R., & Rawlings, J. B. (1993). Model predictive control with linear models. *AIChE Journal, 39*(2), 262–287.
50. Scokaert, P. O. M., Rawlings, J. B., & Meadows, E. S. (1997). Discrete-time stability with perturbations: Application to model predictive control. *Automatica, 33*(3), 463–470.
51. Nevistić, V., & Morari, M. (1996). Robustness of MPC-based schemes for constrained control of nonlinear systems. *IFAC Proceedings Volumes, 29*(1), 5823–5828.
52. Scokaert, P. O. M., & Rawlings, J. B. (1998). Constrained linear quadratic regulation. *IEEE Transactions on Automatic Control, 43*(8), 1163–1169.
53. Grimm, G., Messina, M. J., Tuna, S. E., & Teel, A. R. (2004). Examples when nonlinear model predictive control is nonrobust. *Automatica, 40*(10), 1729–1738.
54. Grimm, G., Messina, M. J., Tuna, S. E., & Teel, A. R. (2007). Nominally robust model predictive control with state constraints. *IEEE Transactions on Automatic Control, 52*(10), 1856–1870.
55. Pannocchia, G., Rawlings, J. B., & Wright, S. J. (2011). Conditions under which suboptimal nonlinear MPC is inherently robust. *Systems & Control Letters, 60*(9), 747–755.
56. Allan, D. A., Bates, C. N., Risbeck, M. J., & Rawlings, J. B. (2017). On the inherent robustness of optimal and suboptimal nonlinear MPC. *Systems & Control Letters, 106*, 68–78.
57. Yu, S., Reble, M., Chen, H., & Allgöwer, F. (2014). Inherent robustness properties of quasi-infinite horizon nonlinear model predictive control. *Automatica, 50*(9), 2269–2280.
58. Qin, S. J., & Badgwell, T. A. (2003). A survey of industrial model predictive control technology. *Control Engineering Practice, 11*(7), 733–764.
59. Mayne, D. Q. (2014). Model predictive control: Recent developments and future promise. *Automatica, 50*(12), 2967–2986.
60. Blanchini, F. (1999). Set invariance in control. *Automatica, 35*(11), 1747–1767.
61. Tøndel, P., Johansen, T. A., & Bemporad, A. (2003). An algorithm for multi-parametric quadratic programming and explicit MPC solutions. *Automatica, 39*(3), 489–497.
62. Karg, B., & Lucia, S. (2020). Efficient representation and approximation of model predictive control laws via deep learning. *IEEE Transactions on Cybernetics, 50*(9), 3866–3878.
63. Berberich, J., Köhler, J., Müller, M. A., & Allgöwer, F. (2022). Linear tracking MPC for nonlinear systems—Parts I and II. *IEEE Transactions on Automatic Control, 67*(9), 4390–4421.
64. Srikanthan, A., Karapetyan, A., Kumar, V., & Matni, N. (2024). Closed-loop analysis of ADMM-based suboptimal linear model predictive control. *IEEE Control Systems Letters, 8*, 3195–3200.
65. Kurula, M., Humaloja, J.-P., & Dubljevic, S. (2025). Region-free explicit model-predictive control for linear systems on Hilbert spaces. *IEEE Transactions on Automatic Control, 70*(1), 518–525.
66. Mattingley, J., & Boyd, S. (2012). CVXGEN: A code generator for embedded convex optimization. *Optimization and Engineering, 13*, 1–27.
67. Ferreau, H. J., Kirches, C., Potschka, A., Bock, H. G., & Diehl, M. (2014). qpOASES: A parametric active-set algorithm for quadratic programming. *Mathematical Programming Computation, 6*(4), 327–363.
68. Borrelli, F., Bemporad, A., & Morari, M. (2017). *Predictive control for linear and hybrid systems*. Cambridge University Press.
69. Bock, H. G., & Plitt, K.-J. (1984). A multiple shooting algorithm for direct solution of optimal control problems. *IFAC Proceedings Volumes, 17*(2), 1603–1608.
70. Stryk, O.: In: Bulirsch, R., Miele, A., Stoer, J.,& Well, K. (1993) (Eds.), Numerical solution of optimal control problems by direct collocation (pp. 129–143). Birkhäuser Basel.
71. Boggs, P. T., & Tolle, J. W. (1995). Sequential quadratic programming. *Acta Numerica, 4*, 1–51.
72. Diehl, M., Bock, H. G., & Schlöder, J. P. (2005). A real-time iteration scheme for nonlinear optimization in optimal feedback

control. *SIAM Journal on Control and Optimization, 43*(5), 1714–1736.
73. Diehl, M., Findeisen, R., Allgöwer, F., Bock, H. G., & Schlöder, J. P. (2005). Nominal stability of real-time iteration scheme for nonlinear model predictive control. *IEE Proceedings-Control Theory and Applications, 152*(3), 296–308.
74. Houska, B., Ferreau, H. J., & Diehl, M. (2011). An auto-generated real-time iteration algorithm for nonlinear MPC in the microsecond range. *Automatica, 47*(10), 2279–2285.
75. Houska, B., Ferreau, H. J., & Diehl, M. (2011). ACADO toolkit—An open-source framework for automatic control and dynamic optimization. *Optimal Control Applications and Methods, 32*(3), 298–312.
76. Andersson, J. A., Gillis, J., Horn, G., Rawlings, J. B., & Diehl, M. (2019). CasADi: A software framework for nonlinear optimization and optimal control. *Mathematical Programming Computation, 11*(1), 1–36.
77. Yu, S., Qu, T., Xu, F., Chen, H., & Hu, Y. (2017). Stability of finite horizon model predictive control with incremental input constraints. *Automatica, 79*, 265–272.
78. Biegler, L. T. (2021). A perspective on nonlinear model predictive control. *Korean Journal of Chemical Engineering, 38*(7), 1317–1332.
79. De Nicolao, G., Magni, L., & Scattolini, R. (1997). Stabilizing predictive control of nonlinear ARX models. *Automatica, 33*(9), 1691–1697.
80. Nikolakopoulou, A., & Braatz, R. D. (2023). Polynomial NARX-based nonlinear model predictive control of modular chemical systems. *Computers & Chemical Engineering, 177*, Article 108272.
81. Hu, Z., Fang, J., Zheng, R., Li, M., Gao, B., & Zhang, L. (2024). Efficient model predictive control of boiler coal combustion based on NARX neutral network. *Journal of Process Control, 134*, Article 103158.
82. Seel, K., Grøtli, E. I., Moe, S., Gravdahl, J. T.,& Pettersen, K. Y. (2021). Neural network-based model predictive control with input-to-state stability. In *2021 American Control Conference (ACC)* (pp. 3556–3563). IEEE.
83. Chen, H., Scherer, C. W.,& Allgöwer, F. (1997). A game theoretic approach to nonlinear robust receding horizon control of constrained systems. In *Proceedings of the 1997 American control conference* (Vol. 5, pp. 3073–3077).
84. Scokaert, P. O., & Mayne, D. Q. (2002). Min-max feedback model predictive control for constrained linear systems. *IEEE Transactions on Automatic Control, 43*(8), 1136–1142.
85. Raimondo, D. M., Limon, D., Lazar, M., Magni, L., & Camacho, E. F. (2009). Min-max model predictive control of nonlinear systems: A unifying overview on stability. *European Journal of Control, 15*(1), 5–21.
86. Kerrigan, E. C., & Maciejowski, J. M. (2004). Feedback min-max model predictive control using a single linear program: Robust stability and the explicit solution. *International Journal of Robust and Nonlinear Control, 14*(4), 395–413.
87. Langson, W., Chryssochoos, I., Raković, S. V., & Mayne, D. Q. (2004). Robust model predictive control using tubes. *Automatica, 40*(1), 125–133.
88. Mayne, D. Q., Seron, M. M., & Raković, S. V. (2005). Robust model predictive control of constrained linear systems with bounded disturbances. *Automatica, 41*(2), 219–224.
89. Raković, S. V., Kouvaritakis, B., Findeisen, R., & Cannon, M. (2012). Homothetic tube model predictive control. *Automatica, 48*(8), 1631–1638.
90. Rakovic, S. V., Kouvaritakis, B., Cannon, M., Panos, C., & Findeisen, R. (2012). Parameterized tube model predictive control. *IEEE Transactions on Automatic Control, 57*(11), 2746–2761.
91. Mayne, D. Q., Raković, S. V., Findeisen, R., & Allgöwer, F. (2006). Robust output feedback model predictive control of constrained linear systems. *Automatica, 42*(7), 1217–1222.
92. Mayne, D. Q., Raković, S. V., Findeisen, R., & Allgöwer, F. (2009). Robust output feedback model predictive control of constrained linear systems: Time varying case. *Automatica, 45*(9), 2082–2087.
93. Cannon, M., Buerger, J., Kouvaritakis, B., & Rakovic, S. (2011). Robust tubes in nonlinear model predictive control. *IEEE Transactions on Automatic Control, 56*(8), 1942–1947.
94. Yu, S., Maier, C., Chen, H., & Allgöwer, F. (2013). Tube MPC scheme based on robust control invariant set with application to Lipschitz nonlinear systems. *Systems & Control Letters, 62*(2), 194–200.
95. Zhang, X., Pan, W., Scattolini, R., Yu, S., & Xu, X. (2022). Robust tube-based model predictive control with Koopman operators. *Automatica, 137*, Article 110114.
96. Raković, S. V., Dai, L., & Xia, Y. (2023). Homothetic tube model predictive control for nonlinear systems. *IEEE Transactions on Automatic Control, 68*(8), 4554–4569.
97. Li, H., & Shi, Y. (2013). Robust distributed model predictive control of constrained continuous-time nonlinear systems: A robustness constraint approach. *IEEE Transactions on Automatic Control, 59*(6), 1673–1678.
98. Dai, L., Lu, Y., Xie, H., Sun, Z., & Xia, Y. (2020). Robust tracking model predictive control with quadratic robustness constraint for mobile robots with incremental input constraints. *IEEE Transactions on Industrial Electronics, 68*(10), 9789–9799.
99. Kothare, M. V., Balakrishnan, V., & Morari, M. (1996). Robust constrained model predictive control using linear matrix inequalities. *Automatica, 32*(10), 1361–1379.
100. Kouvaritakis, B., Rossiter, J. A., & Schuurmans, J. (2000). Efficient robust predictive control. *IEEE Transactions on Automatic Control, 45*(8), 1545–1549.
101. Wan, Z., & Kothare, M. V. (2003). An efficient off-line formulation of robust model predictive control using linear matrix inequalities. *Automatica, 39*(5), 837–846.
102. Lee, Y. I., & Kouvaritakis, B. (2006). Constrained robust model predictive control based on periodic invariance. *Automatica, 42*(12), 2175–2181.
103. Chen, H., & Scherer, C. W. (2006). Moving horizon H_∞ control with performance adaptation for constrained linear systems. *Automatica, 42*(6), 1033–1040.
104. Yu, S., Böhm, C., Chen, H.,& Allgöwer, F. (2010). Robust model predictive control with disturbance invariant sets. In *Proceedings of the 2010 American control conference* (pp. 6262–6267).
105. Schwarm, A. T., & Nikolaou, M. (1999). Chance-constrained model predictive control. *AIChE Journal, 45*(8), 1743–1752.
106. Li, P., Wendt, M., & Wozny, G. (2002). A probabilistically constrained model predictive controller. *Automatica, 38*(7), 1171–1176.
107. Blackmore, L.,& Ono, M. (2009). Convex chance constrained predictive control without sampling. In *AIAA guidance, navigation, and control conference*. https://doi.org/10.2514/6.2009-5876.
108. Li, N., Kolmanovsky, I., & Girard, A. (2021). An analytical safe approximation to joint chance-constrained programming with additive gaussian noises. *IEEE Transactions on Automatic Control, 66*(11), 5490–5497.
109. Bernardini, D., & Bemporad, A. (2009). Scenario-based model predictive control of stochastic constrained linear systems. In *Proceedings of the 48th IEEE conference on decision and control* (pp. 6333–6338).
110. Blackmore, L., Ono, M., Bektassov, A., & Williams, B. C. (2010). A probabilistic particle-control approximation of chance-constrained stochastic predictive control. *IEEE Transactions on Robotics, 26*(3), 502–517.

111. Calafiore, G. C., & Fagiano, L. (2013). Robust model predictive control via scenario optimization. *IEEE Transactions on Automatic Control, 58*(1), 219–224.
112. Calafiore, G. C., & Fagiano, L. (2013). Stochastic model predictive control of LPV systems via scenario optimization. *Automatica, 49*(6), 1861–1866.
113. Mark, C., & Liu, S. (2020). Stochastic MPC with distributionally robust chance constraints. *IFAC-PapersOnLine, 53*(2), 7136–7141.
114. Li, B., Tan, Y., Wu, A.-G., & Duan, G.-R. (2022). A distributionally robust optimization based method for stochastic model predictive control. *IEEE Transactions on Automatic Control, 67*(11), 5762–5776.
115. McAllister, R. D., & Esfahani, P. M. (2025). Distributionally robust model predictive control: Closed-loop guarantees and scalable algorithms. *IEEE Transactions on Automatic Control, 70*(5), 2963–2978.
116. Hewing, L., Kabzan, J., & Zeilinger, M. N. (2020). Cautious model predictive control using Gaussian process regression. *IEEE Transactions on Control Systems Technology, 28*(6), 2736–2743.
117. Shapiro, A., Zhou, E., & Lin, Y. (2023). Bayesian distributionally robust optimization. *SIAM Journal on Optimization, 33*(2), 1279–1304.
118. Adetola, V., DeHaan, D., & Guay, M. (2009). Adaptive model predictive control for constrained nonlinear systems. *Systems & Control Letters, 58*(5), 320–326.
119. Tanaskovic, M., Fagiano, L., & Gligorovski, V. (2019). Adaptive model predictive control for linear time varying MIMO systems. *Automatica, 105*, 237–245.
120. Zhang, K., & Shi, Y. (2020). Adaptive model predictive control for a class of constrained linear systems with parametric uncertainties. *Automatica, 117*, Article 108974.
121. Dhar, A., & Bhasin, S. (2021). Indirect adaptive MPC for discrete-time LTI systems with parametric uncertainties. *IEEE Transactions on Automatic Control, 66*(11), 5498–5505.
122. Gholaminejad, T., Khaki-Sedigh, A., & Bagheri, P. (2017). Direct adaptive model predictive control tuning based on the first-order plus dead time models. *IET Control Theory & Applications, 11*(16), 2858–2869.
123. Saki, S., & Bolandi, H. (2018). Optimal direct adaptive soft switching multi-model predictive control using the gap metric for spacecraft attitude control in a wide range of operating points. *Aerospace Science and Technology, 77*, 235–243.
124. Wright, S. J. (1997). *Primal-dual interior-point methods*. SIAM.
125. Stellato, B., Banjac, G., Goulart, P., Bemporad, A., & Boyd, S. (2020). OSQP: An operator splitting solver for quadratic programs. *Mathematical Programming Computation, 12*(4), 637–672.
126. Liao-McPherson, D., Nicotra, M. M., & Kolmanovsky, I. (2020). Time-distributed optimization for real-time model predictive control: Stability, robustness, and constraint satisfaction. *Automatica, 117*, Article 108973.
127. Liao-McPherson, D., Skibik, T., Leung, J., Kolmanovsky, I., & Nicotra, M. M. (2022). An analysis of closed-loop stability for linear model predictive control based on time-distributed optimization. *IEEE Transactions on Automatic Control, 67*(5), 2618–2625.
128. Hong, J., Guo, L., Na, X., Li, X., Chu, H., Gao, B.,& Chen, H. (2024). Timescale graph-parallel computation and mechanism analysis of economical predictive driving for commercial trucks. In *2024 IEEE intelligent vehicles symposium* (pp. 454–459).
129. Xu, F., Chen, H., Gong, X., & Mei, Q. (2016). Fast nonlinear model predictive control on FPGA using particle swarm optimization. *IEEE Transactions on Industrial Electronics, 63*(1), 310–321.
130. Guo, H., Liu, F., Xu, F., Chen, H., Cao, D., & Ji, Y. (2019). Nonlinear model predictive lateral stability control of active chassis for intelligent vehicles and its FPGA implementation. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 49*(1), 2–13.
131. Xu, F., Guo, Z., Chen, H., Ji, D., & Qu, T. (2022). A custom parallel hardware architecture of nonlinear model-predictive control on FPGA. *IEEE Transactions on Industrial Electronics, 69*(11), 11569–11579.
132. Yu, L., Goldsmith, A.,& Di Cairano, S. (2017). Efficient convex optimization on GPUs for embedded model predictive control. In *Proceedings of the general purpose GPUs* (pp. 12–21).
133. Bishop, A. L., Zhang, J. Z., Gurumurthy, S., Tracy, K.,& Manchester, Z. (2024). ReLU-QP: A GPU-accelerated quadratic programming solver for model-predictive control. In *2024 IEEE international conference on robotics and automation (ICRA)* (pp. 13285–13292).
134. Khusainov, B., Kerrigan, E. C., & Constantinides, G. A. (2019). Automatic software and computing hardware codesign for predictive control. *IEEE Transactions on Control Systems Technology, 27*(5), 2295–2304.
135. Dunbar, W. B., & Caveney, D. S. (2012). Distributed receding horizon control of vehicle platoons: Stability and string stability. *IEEE Transactions on Automatic Control, 57*(3), 620–633.
136. Zheng, Y., Li, S. E., Li, K., Borrelli, F., & Hedrick, J. K. (2017). Distributed model predictive control for heterogeneous vehicle platoons under unidirectional topologies. *IEEE Transactions on Control Systems Technology, 25*(3), 899–910.
137. Halvgaard, R., Vandenberghe, L., Poulsen, N. K., Madsen, H., & Jørgensen, J. B. (2016). Distributed model predictive control for smart energy systems. *IEEE Transactions on Smart Grid, 7*(3), 1675–1682.
138. Ma, M., Zhang, C., Liu, X., & Chen, H. (2017). Distributed model predictive load frequency control of the multi-area power system after deregulation. *IEEE Transactions on Industrial Electronics, 64*(6), 5129–5139.
139. Moroşan, P.-D., Bourdais, R., Dumur, D., & Buisson, J. (2010). Building temperature regulation using a distributed model predictive control. *Energy and Buildings, 42*(9), 1445–1452.
140. Scherer, H. F., Pasamontes, M., Guzmán, J. L., Álvarez, J. D., Camponogara, E., & Normey-Rico, J. E. (2014). Efficient building energy management using distributed model predictive control. *Journal of Process Control, 24*(6), 740–749.
141. Scattolini, R. (2009). Architectures for distributed and hierarchical model predictive control—A review. *Journal of Process Control, 19*(5), 723–731.
142. Chang, T.-H., Nedić, A., & Scaglione, A. (2014). Distributed constrained optimization by consensus-based primal-dual perturbation method. *IEEE Transactions on Automatic Control, 59*(6), 1524–1538.
143. Giselsson, P., Doan, M. D., Keviczky, T., Schutter, B. D., & Rantzer, A. (2013). Accelerated gradient methods and dual decomposition in distributed model predictive control. *Automatica, 49*(3), 829–833.
144. Zhou, L., & Li, S. (2017). Distributed model predictive control for multi-agent flocking via neighbor screening optimization. *International Journal of Robust and Nonlinear Control, 27*(9), 1690–1705.
145. Shorinwa, O., & Schwager, M. (2024). Distributed model predictive control via separable optimization in multiagent networks. *IEEE Transactions on Automatic Control, 69*(1), 230–245.
146. Skarin, P., Eker, J., Kihl, M.,& Årzén, K.-E. (2019). Cloud-assisted model predictive control. In *2019 IEEE international conference on edge computing (EDGE)* (pp. 110–112).
147. Skarin, P., Eker, J., & Årzén, K.-E. (2020). Cloud-based model predictive control with variable horizon. *IFAC-PapersOnLine, 53*(2), 6993–7000.

148. Dai, L., Ma, Y., Gao, R., Wu, J., & Xia, Y. (2023). Cloud-based computational model predictive control using a parallel multi-block ADMM approach. *IEEE Internet of Things Journal, 10*(12), 10326–10343.
149. Li, N., Zhang, K., Li, Z., Srivastava, V., & Yin, X. (2023). Cloud-assisted nonlinear model predictive control for finite-duration tasks. *IEEE Transactions on Automatic Control, 68*(9), 5287–5300.
150. Ma, Y., Dai, L., Yang, H., Zhao, J., Gao, R., & Xia, Y. (2025). Cloud-edge cooperative MPC for large-scale complex systems with input nonlinearity. *IEEE Transactions on Automation Science and Engineering, 22*, 3835–3851.
151. Schulze Darup, M. (2020). In: Farokhi, F. (Ed.), *Encrypted model predictive control in the cloud* (pp. 231–265). Springer.
152. Vahidi-Moghaddam, A., Li, Z., Li, N., Zhang, K., & Wang, Y. (2022). Event-triggered cloud-based nonlinear model predictive control with neighboring extremal adaptations. In *2022 IEEE 61st conference on decision and control* (pp. 3724–3731).
153. Zhang, K., Li, Z., Wang, Y., & Li, N. (2025). Privacy-preserving nonlinear cloud-based model predictive control via affine masking. *Automatica, 171*, Article 111939.
154. Coulson, J., Lygeros, J.,& Dörfler, F. (2019). Data-enabled predictive control: In the shallows of the DeePC. In *2019 18th European control conference* (pp. 307–312).
155. Markovsky, I., & Dörfler, F. (2021). Behavioral systems theory in data-driven analysis, signal processing, and control. *Annual Reviews in Control, 52*, 42–64.
156. Willems, J. C., Rapisarda, P., Markovsky, I., & De Moor, B. L. M. (2005). A note on persistency of excitation. *Systems & Control Letters, 54*(4), 325–329.
157. Berberich, J., Köhler, J., Müller, M. A., & Allgöwer, F. (2021). Data-driven model predictive control with stability and robustness guarantees. *IEEE Transactions on Automatic Control, 66*(4), 1702–1717.
158. Coulson, J., Lygeros, J., & Dörfler, F. (2022). Distributionally robust chance constrained data-enabled predictive control. *IEEE Transactions on Automatic Control, 67*(7), 3289–3304.
159. Huang, L., Zhen, J., Lygeros, J., & Dörfler, F. (2023). Robust data-enabled predictive control: Tractable formulations and performance guarantees. *IEEE Transactions on Automatic Control, 68*(5), 3163–3170.
160. Huang, L., Lygeros, J., & Dörfler, F. (2024). Robust and kernelized data-enabled predictive control for nonlinear systems. *IEEE Transactions on Control Systems Technology, 32*(2), 611–624.
161. Yang, L., Lu, J., Xu, Y., Li, D., & Xi, Y. (2020). Constrained robust model predictive control embedded with a new data-driven technique. *IET Control Theory & Applications, 14*(16), 2395–2405.
162. Yang, L., Li, D., Ma, A., Xi, Y., Pu, Y., & Tan, Y. (2025). Input-mapping based data-driven model predictive control for unknown linear systems via online learning. *International Journal of Robust and Nonlinear Control, 35*(7), 2537–2565.
163. Yang, L., Ma, A., Li, D., & Xi, Y. (2023). Input-mapping based data-driven model predictive control for unknown linear systems with bounded disturbances. *Automatica, 153*, Article 111056.
164. Li, N., Kolmanovsky, I., & Chen, H. (2025). Data-driven moving-horizon control with adaptive disturbance attenuation for constrained systems. *Systems & Control Letters, 196*, Article 106005.
165. Ljung, L. (1999). *System identification: Theory for the user* (2nd ed.). Prentice Hall.
166. Korda, M., & Mezić, I. (2018). Linear predictors for nonlinear dynamical systems: Koopman operator meets model predictive control. *Automatica, 93*, 149–160.
167. Bruder, D., Fu, X., Gillespie, R. B., Remy, C. D., & Vasudevan, R. (2021). Data-driven control of soft robots using Koopman operator theory. *IEEE Transactions on Robotics, 37*(3), 948–961.
168. Mamakoukas, G., Castaño, M. L., Tan, X., & Murphey, T. D. (2021). Derivative-based Koopman operators for real-time control of robotic systems. *IEEE Transactions on Robotics, 37*(6), 2173–2192.
169. Mamakoukas, G., Di Cairano, S.,& Vinod, A. P. (2022). Robust model predictive control with data-driven Koopman operators. In *2022 American control conference* (pp. 3885–3892).
170. Narasingam, A., & Kwon, J.S.-I. (2019). Koopman Lyapunov-based model predictive control of nonlinear chemical process systems. *AIChE Journal, 65*(11), 16743.
171. Patan, K. (2015). Neural network-based model predictive control: Fault tolerance and stability. *IEEE Transactions on Control Systems Technology, 23*(3), 1147–1155.
172. Ren, Y. M., Alhajeri, M. S., Luo, J., Chen, S., Abdullah, F., Wu, Z., & Christofides, P. D. (2022). A tutorial review of neural network modeling approaches for model predictive control. *Computers & Chemical Engineering, 165*, Article 107956.
173. Cheng, L., Liu, W., Hou, Z.-G., Yu, J., & Tan, M. (2015). Neural-network-based nonlinear model predictive control for piezoelectric actuators. *IEEE Transactions on Industrial Electronics, 62*(12), 7717–7727.
174. Salzmann, T., Kaufmann, E., Arrizabalaga, J., Pavone, M., Scaramuzza, D., & Ryll, M. (2023). Real-time neural MPC: Deep learning model predictive control for quadrotors and agile robotic platforms. *IEEE Robotics and Automation Letters, 8*(4), 2397–2404.
175. Mehndiratta, M., Camci, E., & Kayacan, E. (2018). Automated tuning of nonlinear model predictive controller by reinforcement learning. In: *2018 IEEE/RSJ international conference on intelligent robots and systems (IROS)* (pp. 3016–3021).
176. Gros, S., & Zanon, M. (2019). Data-driven economic NMPC using reinforcement learning. *IEEE Transactions on Automatic Control, 65*(2), 636–648.
177. Bøhn, E., Gros, S., Moe, S., & Johansen, T. A. (2021). Reinforcement learning of the prediction horizon in model predictive control. *IFAC-PapersOnLine, 54*(6), 314–320.
178. Martinsen, A. B., Lekkas, A. M., & Gros, S. (2022). Reinforcement learning-based NMPC for tracking control of ASVs: Theory and experiments. *Control Engineering Practice, 120*, Article 105024.
179. Lin, M., Sun, Z., Xia, Y., & Zhang, J. (2023). Reinforcement learning-based model predictive control for discrete-time systems. *IEEE Transactions on Neural Networks and Learning Systems, 35*(3), 3312–3324.
180. Adhau, S., Gros, S., & Skogestad, S. (2024). Reinforcement learning based MPC with neural dynamical models. *European Journal of Control, 80*, Article 101048.
181. Wan, Y., Xu, Q., & Dragičević, T. (2025). Reinforcement learning-based predictive control for power electronic converters. *IEEE Transactions on Industrial Electronics, 72*(5), 5353–5364.
182. Fan, X., Bu, C., Zhao, X., Sui, J., & Mo, H. (2025). Incremental double Q-learning-enhanced MPC for trajectory tracking of mobile robots. *IEEE Transactions on Instrumentation and Measurement, 74*, 1–14.
183. Limon, D., Calliess, J., & Maciejowski, J. M. (2017). Learning-based nonlinear model predictive control. *IFAC-PapersOnLine,50*(1), 7769–7776.
184. Rosolia, U., & Borrelli, F. (2018). Learning model predictive control for iterative tasks. A data-driven control framework. *IEEE Transactions on Automatic Control, 63*(7), 1883–1896.
185. Xu, X., Chen, H., Lian, C., & Li, D. (2018). Learning-based predictive control for discrete-time nonlinear systems with stochastic disturbances. *IEEE Transactions on Neural Networks and Learning Systems, 29*(12), 6202–6213.

186. Koller, T., Berkenkamp, F., Turchetta, M., & Krause, A. (2018). Learning-based model predictive control for safe exploration. In *2018 IEEE conference on decision and control* (pp. 6059–6066).
187. Kabzan, J., Hewing, L., Liniger, A., & Zeilinger, M. N. (2019). Learning-based model predictive control for autonomous racing. *IEEE Robotics and Automation Letters, 4*(4), 3363–3370.
188. Chen, H., & Guo, L. (2023). Convergence of adaptive MPC for linear stochastic systems. *Science China Information Sciences, 66*, Article 152201.
189. Hertneck, M., Köhler, J., Trimpe, S., & Allgöwer, F. (2018). Learning an approximate model predictive controller with guarantees. *IEEE Control Systems Letters, 2*(3), 543–548.
190. Maiworm, M., Limon, D., & Findeisen, R. (2021). Online learning-based model predictive control with gaussian process models and stability guarantees. *International Journal of Robust and Nonlinear Control, 31*(18), 8785–8812.
191. Gros, S., & Zanon, M. (2022). Learning for MPC with stability & safety guarantees. *Automatica, 146*, Article 110598.
192. Mishra, P. K., Gasparino, M. V., & Chowdhary, G. (2025). Deep model predictive control with stability guarantees. *IEEE Transactions on Automatic Control, 70*(8), 5460–5467.
193. Nascimento, T. P., Dórea, C. E. T., & Gonçalves, L. M. G. (2018). Nonholonomic mobile robots' trajectory tracking model predictive control: A survey. *Robotica, 36*(5), 676–696.
194. Yao, Y., & Shekhar, D. K. (2021). State of the art review on model predictive control (MPC) in heating ventilation and air-conditioning (HVAC) field. *Building and Environment, 200*, Article 107952.
195. Weiss, A., Baldwin, M., Erwin, R. S., & Kolmanovsky, I. (2015). Model predictive control for spacecraft rendezvous and docking: Strategies for handling constraints and case studies. *IEEE Transactions on Control Systems Technology, 23*(4), 1638–1647.
196. Saccani, D., Cecchin, L., & Fagiano, L. (2023). Multitrajectory model predictive control for safe UAV navigation in an unknown environment. *IEEE Transactions on Control Systems Technology, 31*(5), 1982–1997.
197. Chen, Y., Rosolia, U., Ubellacker, W., Csomay-Shanklin, N., & Ames, A. D. (2022). Interactive multi-modal motion planning with branch model predictive control. *IEEE Robotics and Automation Letters, 7*(2), 5365–5372.
198. Bhardwaj, M., Sundaralingam, B., Mousavian, A., Ratliff, N. D., Fox, D., Ramos, F., & Boots, B. (2022). STORM: An integrated framework for fast joint-space model-predictive control for reactive manipulation. In *Proceedings of the conference on robot learning* (Vol. 164, pp. 750–759).
199. Meduri, A., Shah, P., Viereck, J., Khadiv, M., Havoutis, I., & Righetti, L. (2023). BiConMP: A nonlinear model predictive control framework for whole body motion planning. *IEEE Transactions on Robotics, 39*(2), 905–922.
200. Grandia, R., Jenelten, F., Yang, S., Farshidian, F., & Hutter, M. (2023). Perceptive locomotion through nonlinear model-predictive control. *IEEE Transactions on Robotics, 39*(5), 3402–3421.
201. Lin, S., De Schutter, B., Xi, Y., & Hellendoorn, H. (2011). Fast model predictive control for urban road networks via MILP. *IEEE Transactions on Intelligent Transportation Systems, 12*(3), 846–856.
202. Lin, S., De Schutter, B., Xi, Y., & Hellendoorn, H. (2012). Efficient network-wide model-based predictive control for urban traffic networks. *Transportation Research Part C: Emerging Technologies, 24*, 122–140.
203. Sciarretta, A., & Vahidi, A. (2020). *Energy-efficient driving of road vehicles*. Springer.
204. Borhan, H., Vahidi, A., Phillips, A. M., Kuang, M. L., Kolmanovsky, I. V., & Di Cairano, S. (2012). MPC-based energy management of a power-split hybrid electric vehicle. *IEEE Transactions on Control Systems Technology, 20*(3), 593–603.
205. Cairano, S. D., Bernardini, D., Bemporad, A., & Kolmanovsky, I. V. (2014). Stochastic MPC with learning for driver-predictive vehicle control and its application to HEV energy management. *IEEE Transactions on Control Systems Technology, 22*(3), 1018–1031.
206. Guo, L., Gao, B., Gao, Y., & Chen, H. (2017). Optimal energy management for HEVs in eco-driving applications using bi-level MPC. *IEEE Transactions on Intelligent Transportation Systems, 18*(8), 2153–2162.
207. Kamal, M. A. S., Mukai, M., Murata, J., & Kawabe, T. (2011). Ecological driving based on preceding vehicle prediction using MPC. *IFAC Proceedings Volumes, 44*(1), 3843–3848.
208. Chen, H., Guo, L., Ding, H., Li, Y., & Gao, B. (2019). Real-time predictive cruise control for eco-driving taking into account traffic constraints. *IEEE Transactions on Intelligent Transportation Systems, 20*(8), 2858–2868.
209. Wang, S., & Lin, X. (2020). Eco-driving control of connected and automated hybrid vehicles in mixed driving scenarios. *Applied Energy, 271*, Article 115233.
210. Yan, Y., Li, N., Hong, J., Gao, B., Zhang, J., Chen, H., Sun, J., & Song, Z. (2023). Eco-coasting controller using road grade preview: Evaluation and online implementation based on mixed integer model predictive control. *IEEE Transactions on Vehicular Technology, 72*(10), 12508–12523.
211. Dong, S., Chen, H., Gao, B., Guo, L., & Liu, Q. (2022). Hierarchical energy-efficient control for CAVs at multiple signalized intersections considering queue effects. *IEEE Transactions on Intelligent Transportation Systems, 23*(8), 11643–11653.
212. Leng, J., Sun, C., Dong, H., Li, D., Zhang, C., & Chen, P. C. Y. (2025). Adaptive eco-driving with guided speed planning and lane changing through signalized intersections. *IEEE Transactions on Transportation Electrification, 11*(3), 8365–8376.
213. He, C. R.,& Li, N. (2024). Eco-driving accounting for interactive cut-in vehicles. In *2024 IEEE international conference on mobility, operations, services and technologies (MOST)* (pp. 90–100).
214. Stanger, T., & Re, L. (2013). A model predictive cooperative adaptive cruise control approach. In *2013 American control conference* (pp. 1374–1379).
215. Turri, V., Besselink, B., & Johansson, K. H. (2017). Cooperative look-ahead control for fuel-efficient and safe heavy-duty vehicle platooning. *IEEE Transactions on Control Systems Technology, 25*(1), 12–28.
216. Kazemi, H., Mahjoub, H. N., Tahmasbi-Sarvestani, A., & Fallah, Y. P. (2018). A learning-based stochastic MPC design for cooperative adaptive cruise control to handle interfering vehicles. *IEEE Transactions on Intelligent Vehicles, 3*(3), 266–275.
217. Wang, P., Deng, H., Zhang, J., Wang, L., Zhang, M., & Li, Y. (2022). Model predictive control for connected vehicle platoon under switching communication topology. *IEEE Transactions on Intelligent Transportation Systems, 23*(7), 7817–7830.
218. Hu, M., Li, C., Bian, Y., Zhang, H., Qin, Z., & Xu, B. (2022). Fuel economy-oriented vehicle platoon control using economic model predictive control. *IEEE Transactions on Intelligent Transportation Systems, 23*(11), 20836–20849.
219. Liu, C., Lee, S., Varnhagen, S., & Tseng, H. E. (2017). Path planning for autonomous vehicles using model predictive control. In *2017 IEEE intelligent vehicles symposium* (pp. 174–179).
220. Suh, J., Chae, H., & Yi, K. (2018). Stochastic model-predictive control for lane change decision of automated driving vehicles. *IEEE Transactions on Vehicular Technology, 67*(6), 4771–4782.
221. Brüdigam, T., Olbrich, M., Wollherr, D., & Leibold, M. (2023). Stochastic model predictive control with a safety guarantee for automated driving. *IEEE Transactions on Intelligent Vehicles, 8*(1), 22–36.

222. Liu, K., Li, N., Tseng, H. E., Kolmanovsky, I., & Girard, A. (2023). Interaction-aware trajectory prediction and planning for autonomous vehicles in forced merge scenarios. *IEEE Transactions on Intelligent Transportation Systems, 24*(1), 474–488.
223. Nair, S. H., Lee, H., Joa, E., Wang, Y., Tseng, H. E., & Borrelli, F. (2025). Predictive control for autonomous driving with uncertain, multimodal predictions. *IEEE Transactions on Control Systems Technology, 33*(4), 1178–1192.
224. Lian, C., Xu, X., Chen, H., & He, H. (2016). Near-optimal tracking control of mobile robots via receding-horizon dual heuristic programming. *IEEE Transactions on Cybernetics, 46*(11), 2484–2496.
225. Guo, H., Shen, C., Zhang, H., Chen, H., & Jia, R. (2018). Simultaneous trajectory planning and tracking using an MPC method for cyber-physical systems: A case study of obstacle avoidance for an intelligent vehicle. *IEEE Transactions on Industrial Informatics, 14*(9), 4273–4283.
226. Guo, H., Liu, J., Cao, D., Chen, H., Yu, R., & Lv, C. (2018). Dual-envelop-oriented moving horizon path tracking control for fully automated vehicles. *Mechatronics, 50*, 422–433.
227. Guo, H., Cao, D., Chen, H., Sun, Z., & Hu, Y. (2019). Model predictive path following control for autonomous cars considering a measurable disturbance: Implementation, testing, and verification. *Mechanical Systems and Signal Processing, 118*, 41–60.
228. Wang, H., Liu, B., Ping, X., & An, Q. (2019). Path tracking control for autonomous vehicles based on an improved MPC. *IEEE Access, 7*, 161064–161073.
229. Cao, J., Song, C., Peng, S., Song, S., Zhang, X., & Xiao, F. (2020). Trajectory tracking control algorithm for autonomous vehicle considering cornering characteristics. *IEEE Access, 8*, 59470–59484.
230. Zuo, Z., Yang, X., Li, Z., Wang, Y., Han, Q., Wang, L., & Luo, X. (2021). MPC-based cooperative control strategy of path planning and trajectory tracking for intelligent vehicles. *IEEE Transactions on Intelligent Vehicles, 6*(3), 513–522.
231. Zhang, K., Sun, Q., & Shi, Y. (2021). Trajectory tracking control of autonomous ground vehicles using adaptive learning MPC. *IEEE Transactions on Neural Networks and Learning Systems, 32*(12), 5554–5564.
232. Chu, D., Li, H., Zhao, C., & Zhou, T. (2023). Trajectory tracking of autonomous vehicle based on model predictive control with PID feedback. *IEEE Transactions on Intelligent Transportation Systems, 24*(2), 2239–2250.
233. Mehra, R. K., Amin, J. N., Hedrick, K. J., Osorio, C., & Gopalasamy, S. (1997). Active suspension using preview information and model predictive control. In *Proceedings of the 1997 IEEE international conference on control applications* (pp. 860–865).
234. Borrelli, F., Falcone, P., Keviczky, T., & Asgari, J. (2005). MPC-based approach to active steering for autonomous vehicle systems. *International Journal of Vehicle Autonomous Systems, 3*(2–4), 265–291.
235. Falcone, P., Borrelli, F., Asgari, J., Tseng, H. E., & Hrovat, D. (2007). Predictive active steering control for autonomous vehicle systems. *IEEE Transactions on Control Systems Technology, 15*(3), 566–580.
236. Falcone, P., Tseng, H. E., Borrelli, F., Asgari, J., & Hrovat, D. (2008). MPC-based yaw and lateral stabilisation via active front steering and braking. *Vehicle System Dynamics, 46*(sup1), 611–628.
237. Ren, B., Chen, H., Zhao, H., & Yuan, L. (2016). MPC-based yaw stability control in in-wheel-motored EV via active front steering and motor torque distribution. *Mechatronics, 38*, 103–114.
238. Canale, M., Milanese, M., & Novara, C. (2006). Semi-active suspension control using fast model-predictive techniques. *IEEE Transactions on Control Systems Technology, 14*(6), 1034–1046.
239. Giorgetti, N., Bemporad, A., Tseng, H. E., & Hrovat, D. (2006). Hybrid model predictive control application towards optimal semi-active suspension. *International Journal of Control, 79*(5), 521–533.
240. Theunissen, J., Sorniotti, A., Gruber, P., Fallah, S., Ricco, M., Kvasnica, M., & Dhaens, M. (2020). Regionless explicit model predictive control of active suspension systems with preview. *IEEE Transactions on Industrial Electronics, 67*(6), 4877–4888.
241. Papadimitrakis, M., & Alexandridis, A. (2022). Active vehicle suspension control using road preview model predictive control and radial basis function networks. *Applied Soft Computing, 120*, Article 108646.
242. Ataei, M., Khajepour, A., & Jeon, S. (2020). Model predictive control for integrated lateral stability, traction/braking control, and rollover prevention of electric vehicles. *Vehicle System Dynamics, 58*(1), 49–73.
243. Zhang, L., Chen, H., Huang, Y., Guo, H., Sun, H., Ding, H., & Wang, N. (2020). Model predictive control for integrated longitudinal and lateral stability of electric vehicles with in-wheel motors. *IET Control Theory & Applications, 14*(18), 2741–2751.
244. Li, N., Girard, A., & Kolmanovsky, I. (2019). Stochastic predictive control for partially observable Markov decision processes with time-joint chance constraints and application to autonomous vehicle control. *Journal of Dynamic Systems, Measurement, and Control, 141*(7), Article 071007.
245. Li, N., Kolmanovsky, I., & Girard, A. (2020). Detection-averse optimal and receding-horizon control for Markov decision processes. *Automatica, 122*, Article 109278.
246. Zanon, M., Gros, S., & Palladino, M. (2022). Stability-constrained Markov decision processes using MPC. *Automatica, 143*, Article 110399.
247. Gros, S., & Zanon, M. (2022). Economic MPC of Markov decision processes: Dissipativity in undiscounted infinite-horizon optimal control. *Automatica, 146*, Article 110602.
248. Sunberg, Z., Chakravorty, S., & Erwin, R. S. (2013). Information space receding horizon control. *IEEE Transactions on Cybernetics, 43*(6), 2255–2260.
249. Sunberg, Z., Chakravorty, S., & Erwin, R. S. (2016). Information space receding horizon control for multisensor tasking problems. *IEEE Transactions on Cybernetics, 46*(6), 1325–1336.
250. Papachristos, C., Khattak, S., & Alexis, K. (2017). Uncertainty-aware receding horizon exploration and mapping using aerial robots. In *2017 IEEE international conference on robotics and automation (ICRA)* (pp. 4568–4575).
251. Xu, T. (2024). Recent advances in rapidly-exploring random tree: A review. *Heliyon, 10*(11), 32451.
252. Hafner, D., Lillicrap, T., Ba, J., & Norouzi, M. (2020). Dream to control: Learning behaviors by latent imagination. In *International conference on learning representations (ICLR)*.
253. Hafner, D., Pasukonis, J., Ba, J., & Lillicrap, T. (2025). Mastering diverse control tasks through world models. *Nature, 640*, 647–653.
254. Schrittwieser, J., Antonoglou, I., Hubert, T., Simonyan, K., Sifre, L., Schmitt, S., Guez, A., Lockhart, E., Hassabis, D., & Graepel, T. (2020). Mastering Atari, Go, chess and shogi by planning with a learned model. *Nature, 588*, 604–609.
255. Matsuo, Y., LeCun, Y., Sahani, M., Precup, D., Silver, D., Sugiyama, M., Uchibe, E., & Morimoto, J. (2022). Deep learning, reinforcement learning, and world models. *Neural Networks, 152*, 267–275.
256. Ding, J., Zhang, Y., Shang, Y., Zhang, Y., Zong, Z., Feng, J., Yuan, Y., Su, H., Li, N., Sukiennik, N., Xu, F., & Li, Y. (2025). Understanding world or predicting future? A comprehensive survey of world models. *ACM Computing Surveys, 58(3), 1–38*.
257. Nagabandi, A., Konolige, K., Levine, S.,& Kumar, V. (2020). Deep dynamics models for learning dexterous manipulation. In

Proceedings of the conference on robot learning (Vol. 100, pp. 1101–1112).
258. Hansen, N., Su, H., & Wang, X. (2024) TD-MPC2: Scalable, robust world models for continuous control. In *International conference on learning representations (ICLR)*.
259. LeCun, Y. (2022). A path towards autonomous machine intelligence. *Open Review, 6*, 1–62.
260. Gumbsch, C., Sajid, N., Martius, G., & Butz, M. V. (2024). Learning hierarchical world models with adaptive temporal abstractions from discrete latent dynamics. In *International conference on learning representations (ICLR)*.
261. Hirose, N., Xia, F., Martín-Martín, R., Sadeghian, A., & Savarese, S. (2019). Deep visual MPC-policy learning for navigation. *IEEE Robotics and Automation Letters, 4*(4), 3184–3191.
262. Ebert, F., Finn, C., Dasari, S., Xie, A., Lee, A., & Levine, S. (2018). Visual foresight: Model-based deep reinforcement learning for vision-based robotic control. arXiv preprint arXiv:1812.00568
263. Li, S., & Bastani, O. (2020). Robust model predictive shielding for safe reinforcement learning with stochastic dynamics. In *2020 IEEE international conference on robotics and automation (ICRA)* (pp. 7166–7172).
264. Li, Y., Li, N., Tseng, H. E., Girard, A., Filev, D., & Kolmanovsky, I. (2021). Safe reinforcement learning using robust action governor. In *Proceedings of the 3rd conference on learning for dynamics and control* (Vol. 144, pp. 1093–1104).
265. Zanon, M., & Gros, S. (2021). Safe reinforcement learning using robust MPC. *IEEE Transactions on Automatic Control, 66*(8), 3638–3652.
266. Wabersich, K. P., & Zeilinger, M. N. (2021). A predictive safety filter for learning-based control of constrained nonlinear dynamical systems. *Automatica, 129*, Article 109597.
267. Wabersich, K. P., Hewing, L., Carron, A., & Zeilinger, M. N. (2022). Probabilistic model predictive safety certification for learning-based control. *IEEE Transactions on Automatic Control, 67*(1), 176–188.
268. Wabersich, K. P., & Zeilinger, M. N. (2023). Predictive control barrier functions: Enhanced safety mechanisms for learning-based control. *IEEE Transactions on Automatic Control, 68*(5), 2638–2651.
269. Yuan, K., Huang, Y., Yang, S., Zhou, Z., Wang, Y., Cao, D., & Chen, H. (2024). Evolutionary decision-making and planning for autonomous driving based on safe and rational exploration and exploitation. *Engineering, 33*, 108–120.
270. Lotfi, F., Virji, K., Faraji, F., Berry, L., Holliday, A., Meger, D., & Dudek, G. (2024). Uncertainty-aware hybrid paradigm of nonlinear MPC and model-based RL for offroad navigation: Exploration of transformers in the predictive model. In *2024 IEEE international conference on robotics and automation (ICRA)* (pp. 2925–2931).

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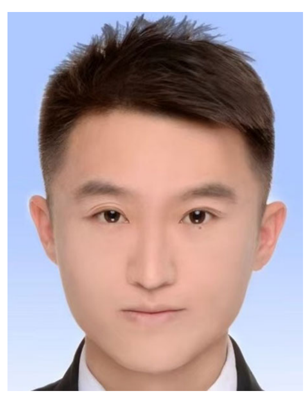

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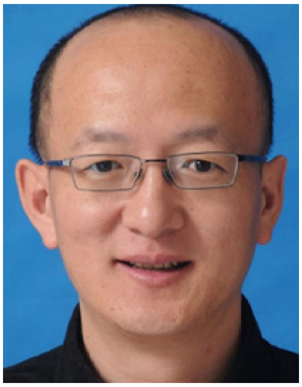

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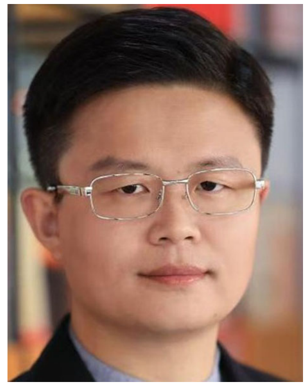

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