Advanced Control Solutions Towards Resource Efficient Production

Literature Review

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MPC and its Variants

As modern industrial systems grow in complexity, the need for intelligent, reliable, and resource-aware control strategies becomes increasingly urgent. Traditional feedback control methods, while robust and well understood, often struggle to meet the demands of real-time implementation under tight energy and computational constraints. This has led to the widespread adoption of Model Predictive Control (MPC), a method that predicts a future system behavior by solving an optimization problem over a finite horizon at each time step.

MPC is able to handle constraints and multivariable systems by design. However, this comes at the cost of substantial computational demand. The fundamental principles of convex optimization, as described by Boyd and Vandenberghe [10], are at the mathematical basis of nominal MPC formulation. But in practice, solving these problems online is often problematic for systems with limited computational resources.

Conventional MPC often relies on iterative online optimisation, demanding substantial computational resources and deemed unsuitable for industrial hardware with limited computational capacity [40]. Real-time changes in control performance, i.e., online tunability, are often required in industrial plants. Static, implicit MPC can struggle with varying conditions [11, 37]. However, the implementation of the tunability underlines existing problems of MPC with computational requirements [48]. The reason is that in MPC, the real-time tunability requires updating the weighting matrices in the objective function, which then leads to a whole different set of implementation issues, which are mainly memory requirements and safety guarantees [27, 44].

In recent years, new developments have sought to expand the applicability of MPC while addressing its limitations [26, 39]. For instance, Borrelli [9] offers a comprehensive treatment of constrained optimal control, including techniques to enforce recursive feasibility and stability, both of which are crucial in safety-critical applications. Bemporad et al. [1] proposed explicit MPC (EMPC), which precomputes the control law offline and stores it as a piecewise affine function. This dramatically reduces online computation but introduces memory issues and suffers from scalability limitations. The work [35] remains a foundational reference for predictive control, detailing both its theoretical advantages and practical hurdles.

Another strand of research focuses on ensuring stability despite approximations. Zhang [36] discusses the use of terminal cost functions and invariant sets to guarantee stability, a strategy we also adopt in ACTREP recursive control schemes. Sampling-based techniques, such as random shooting, have proven particularly effective. These methods avoid solving optimization problems by exploring a set of control trajectories and selecting the one with the best predicted cost [19].

At the same time, data-driven approaches have become increasingly relevant. Adhau et al. [2] and

Kenefake et al. [25] explore reinforcement learning and neural network approximators for MPC, highlighting both their potential and the challenges in guaranteeing robust behavior.

Neural approximations of MPC laws form another promising direction. Instead of evaluating optimization problems online, controllers are represented as trained networks that emulate MPC behavior, typically by supervised learning on trajectory datasets [46]. However, ensuring stability and constraint satisfaction in such learned controllers remains an open challenge.

To overcome this limitation, EMPC is often replaced by neural network (NN) approximations. In comparison to EMPC [6], the storage requirements for the NN-based controller are negligible [32]. Furthermore, the computation of control inputs is boiled down to an evaluation of one function, eliminating the need to solve potentially time-consuming point location problems. While this eases the computational burden, it comes at the price of sacrificing the stability guarantees [33].

Online adaptation and regularization further improve the robustness of approximated controllers. For example, updates to policy parameters based on real-time feedback can mitigate degradation due to model mismatch [18], while enforcing conservative safety margins adds a second layer of protection [21].

Robust formulations like tube-based MPC, developed by Mayne et al. [38], ensure constraint satisfaction in the face of bounded disturbances by wrapping nominal trajectories in invariant tubes. Simplification methods, including move blocking [12] and adaptive horizon techniques [29], further reduce computational complexity and adapt controller effort to system behavior dynamically.

The ACTREP project builds on these contributions. Our goal is to develop control strategies that retain the strengths of MPC — prediction, constraint handling, and performance — while enabling real-time feasibility on embedded systems. This requires innovative approximations, structured sampling, and a deep integration of theoretical insights with hardware-aware design [3, 6, 8, 50].

Energy-Efficient Control Methods

Energy-aware control is increasingly important in the design of industrial control systems, especially where environmental targets pose limitations on energy use. MPC, effective in handling constraints and multivariable dynamics, has evolved to address energy efficiency as a core performance objective.

Several predictive strategies have been proposed to embed energy consumption directly into the control cost function [13, 25]. These methods balance performance and power usage, enabling real-time decision-making that respects resource constraints. For instance, certain MPC variants consider thermal behavior in actuators and processes [2], ensuring not only state regulation but also minimization of waste heat.

Approaches that optimize for power consumption while preserving constraint satisfaction have demonstrated improvements in long-term operational cost [12]. Others explore trade-offs between performance metrics and energy profiles, resulting in adaptive schemes that tune control aggressiveness according to power availability [29]. Some methods have been extended to account for dynamic energy pricing or demand-side flexibility, integrating economic signals into control policies [15, 35]. This is especially relevant in smart manufacturing or energy markets where real-time adaptation leads to cost savings.

The tool proposed in [47], known as TuneMPC, provides a systematic framework for the economic tuning of tracking (nonlinear) MPC problems. By explicitly incorporating economic cost terms and allowing structured trade-offs between tracking accuracy and resource consumption, TuneMPC facilitates application-specific customization of the MPC objective.

In embedded systems, energy-efficient control is also about computational simplicity. Techniques that reduce the solver burden—such as neural approximations or sampling-based planning—directly impact power draw in microcontrollers and edge devices [1].

In the context of ACTREP, we adopt these principles by ensuring that even low-power platforms can execute our control approximations.

Approximated and Solver-Free Control

In real-time control applications, especially those involving fast dynamics or embedded platforms, the computational demands of classical MPC often exceed what is practical. To bridge this gap, researchers have developed approximated and solver-free control architectures that prioritize execution speed while maintaining acceptable control quality.

Sampling-based techniques, such as random shooting, have proven particularly effective. These methods avoid solving optimization problems by exploring a set of control trajectories and selecting the one with the best predicted cost [4].

Recent advances incorporate hybrid architectures—combining learned feedback or sample-based technique policies with fallback, i.e. support controllers or invariant sets to provide stability guarantees when approximations deviate from expected behavior [3, 33]. These frameworks ensure that, even in the presence of modeling errors, the system remains within safe bounds.

Neural network approximations of MPC policies have gained traction for their ability to significantly reduce online computation, making them suitable for deployment on embedded platforms with limited resources. As shown in [22], explicit MPC laws can be exactly captured using deep ReLU-based architectures, and theoretical bounds are given for the necessary network size. However, this work does not address the reliability of the approximation, especially in terms of safety. Follow-up research in [23] introduces a verification framework that leverages output range analysis and mixed-integer optimization to certify safety for fixed NN controllers under parametric uncertainty. Although this approach yields compact control representations and reduces memory usage, it lacks any mechanism for online adjustment of control performance.

The method proposed in [45] tackles robust feasibility and stability by introducing a safety filter that projects NN outputs onto feasible sets. While this enhances reliability, it still relies on solving parametric QPs online, which undermines efforts toward fully solver-free implementation. Alternatively, the training scheme in [49] focuses on optimizing closed-loop performance through learning under uncertainty, yet it does not offer guarantees for constraint satisfaction and involves nontrivial training complexity.

Across these methods [22, 23, 45, 49], a common limitation is the lack of flexibility: changes in cost function weights necessitate retraining the network or regenerating the dataset, as the underlying optimal control law shifts. This restricts their use in applications requiring runtime adaptation of control behavior. By contrast, the approach presented here enables real-time tunability via convex interpolation between pre-trained NN controllers. This allows continuous adjustment of performance objectives while retaining guarantees of constraint satisfaction and closed-loop stability

Online adaptation and regularization further improve the robustness of approximated controllers. For example, updates to policy parameters based on real-time feedback can mitigate degradation due to model mismatch [18], while enforcing conservative safety margins adds a second layer of protection [21].

ACTREP methodology is based on these solver-free alternatives. Our framework enables MPC-like control on platforms where conventional optimization-based approaches would fail to meet timing and energy constraints.

Stability and Recursive Feasibility

Stability and recursive feasibility are essential properties for any control scheme intended for real-world deployment, especially in safety-critical and regulated environments. MPC, while effective, must be carefully designed to ensure that control actions do not lead the system into unsafe or infeasible operating regions over time [43].

A common approach to enforcing stability involves augmenting the MPC cost function with a terminal penalty and including a terminal constraint that maps to an invariant set [17, 37]. These methods ensure that the closed-loop system returns to a known, safe region even under bounded disturbances or modeling errors.

Lyapunov-based techniques [34] offer formal guarantees of convergence and constraint satisfaction. In particular, constructive Lyapunov functions have been employed to design MPC schemes that are not only stabilizing but also robust to parameter uncertainty.

Another line of research uses robust feasibility updates during runtime. Here, the feasible region is tightened online based on current estimation accuracy and predicted system evolution [51]. These techniques allow for the incorporation of real-time information while preserving theoretical guarantees.

In ACTREP, we take a similar approach by embedding stabilizing support controllers into the control architecture. These act as a safety net, ensuring recursive feasibility even when sampling-based or approximated methods are employed. The integration of robust constraint tightening with structured fallback layers enables safe, real-time control under hardware and modeling limitations [7, 9, 28, 41, 42].

Embedded Implementation

The practical realization of advanced control algorithms relies on their compatibility with embedded hardware. While theoretical results for MPC are well-established, deployment on resource-constrained platforms such as microcontrollers, FPGAs, or edge devices introduces nontrivial challenges [52].

Early solutions attempted to shrink problem dimensions or increase sampling periods, but these measures often degraded performance. Instead, algorithmic simplifications and tailored numerical solvers have become the standard response. Fast gradient methods and customized QP solvers, such as those targeting single-core, fixed-point architectures, allow for sub-millisecond computation cycles [16].

Another line of work emphasizes pre-compilation and offline policy generation. Controllers that utilize explicit MPC or regression-based approximations avoid online optimization entirely, trading memory for speed [20]. Though powerful, these methods demand careful quantization and region management, especially in high-dimensional systems [5].

Parallel advances in hardware-aware software design now allow full-stack optimization of controller structure and platform constraints. Work such as [30] demonstrates how modern toolchains can generate optimized C code from symbolic models, tightly coupling algorithm design to low-level execution.

In addition, high-speed architectures like GPUs and FPGAs enable sophisticated controllers on real-time timelines. These platforms offer determinism and parallelization but require more intricate design validation and tool familiarity [14]. Importantly, their suitability depends on the energy budget and application scale.

To meet the demands of portable and networked devices, low-power designs that limit memory access and floating-point usage have also emerged. Controller implementations that adapt resolution or switch modes based on processor load show promise in this space [4].

Beyond computational capacity, control deployment must account for scheduling, communication delays, and operating system interactions. This is especially true in systems that combine diagnostic layers, remote updates, and cloud-based supervision [44].

ACTREP addresses these constraints with a two-tiered control architecture: a lightweight approximated controller executes on the main cycle, while a backup support controller ensures safety under timing faults [24]. This approach allows our solver-free MPC formulations to function within 0.01 s deadlines on 168 MHz STM32 cores, matching the responsiveness needed for experimental deployment.

Experimental validation is central to ACTREP's embedded philosophy. We implement and test our controllers on real-world setups, including modular platforms designed for rapid prototyping [31]. Our experiments confirm that aggressive approximations, when properly stabilized, provide significant computational savings without loss of closed-loop performance.

The runtime system also incorporates monitoring routines to detect approximation drift and switch to conservative fallback behavior as needed. Inspired by safety standards in embedded software, these routines form the basis of certification pathways [53].

Ultimately, the success of embedded deployment hinges on careful integration between theoretical control logic and hardware-aware constraints. The insights from [44] and similar studies have informed our system architecture, enabling scalable, certifiable, and energy-aware deployment of ACTREP's control logic in embedded environments.

Conclusion

This literature review has mapped the recent advanced control strategies with a focus on energy efficiency, solver-free approximations, theoretical guarantees, and embedded implementation—each critical to ACTREP. While Model Predictive Control (MPC) remains a powerful framework, its practical limitations on embedded platforms have inspired the creation of explicit formulations, neural approximations and hybrid fallback strategies.

However, these developments rarely come without trade-offs. Methods that ease computational burdens often do so at the expense of stability guarantees or runtime flexibility. Neural network-based control, for example, can approximate MPC behavior efficiently but still struggles to offer safety assurances with extensive traing required. Similarly, sampling-based methods show promise, yet they need fallback designs and real-time monitoring.

ACTREP attemps to preserve the predictive strength and constraint handling of classical MPC while making the architecture certifiably lightweight and deployable on real-time hardware. Whether this balance can be maintained across diverse applications remains an open question.

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