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Review

An outlook on robust model predictive control algorithms: Reflections on performance and computational aspects☆

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ABSTRACT

In this paper, we discuss the model predictive control algorithms that are tailored for uncertain systems. Robustness notions with respect to both deterministic (or set based) and stochastic uncertainties are discussed and contributions are reviewed in the model predictive control literature. We present, classify and compare different notions of the robustness properties of state of the art algorithms, while a substantial emphasis is given to the closed-loop performance and computational complexity properties. Furthermore, connections between (i) the theory of risk and (ii) robust optimization research areas and robust model predictive control are discussed. Lastly, we provide a comparison of current robust model predictive control algorithms via simulation examples illustrating closed loop performance and computational complexity features.

Contents

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1. Introduction

1.1. General Outline

Model predictive control (MPC) technology is a mature research field developed over four decades both in industry and academia addressing the question of (practical) optimal control of dynamical systems under process constraints and economic incentives. Its popularity is mainly attributed to two significant properties of MPC algorithms; first one is the (explicit) constraint handling capabilities while providing (sub-)optimal operation, see, e.g., [1–3]; and the second superiority is the ease of extending the algorithms to multi-input multi-output (MIMO) systems. Many different approaches were developed, such as; Model Algorithmic Control in 1978 [4], with finite impulse response models, Dynamic Matrix Control in 1980 [5], with step response models, Generalized Predictive Control in 1987 [6], with transfer function models. Lately, MPC methods developed by considering the state-space models have become the standard way of formulating predictive control problems. Throughout the different algorithms, however, the essence of predictive control is the same and can be stated as, [7], optimizing over manipulated inputs to control the forecasts of future process behaviour. Stated rigorously, [8,9], MPC is a form of control in which the current control action is obtained by solving, at each sampling instant, a finite or infinite horizon open-loop optimal control problem. In this technique an optimal control sequence is obtained by using the current state of the plant as the initial state of the plant and the first control in this sequence is applied to the plant, while at the next sampling (or decision) instant the whole procedure is repeated.

The process of selecting an optimal control action can be summarized in two distinct steps [10,11],

(i) shaping the beliefs of future output performances (forecasts);
(ii) the choice of to-be-applied control action as a function of these forecasts.

A general approach to obtain output forecasts is through dynamic models describing the process behaviour. During the initial development of MPC, empirical linear input-output models were utilized. If the operating window is relatively small, such models are proved to be sufficient. However, if the operating conditions vary drastically, e.g., batch processes, then nonlinear models should be used, which effects the complexity of the MPC problem.[1] In either case the developed models will be far from perfect; leading to mismatch between the forecasts and the true behaviour. As a result, the commissioned MPC controllers are kept non-operational frequently due to the model deterioration or lack of maintenance of the model, [14]. It is both natural and logical to include the effect of (modeled) uncertainty into the prediction model, hence into the optimal control action. In different words, selecting a control action on the basis of the nominal forecasts leads to an undesired operation due to definite dispersion from the expectations in the controlled variables. However, uncertainty also radically effects the optimal control actions in closed-loop predictions, casting them to become pessimistic (or aggressive), hence the resulting performance levels are also effected [15].

A well-established way to overcome or reduce the effects of uncertainty is by applying feedback techniques. In many instances, robust control theory [16] provides *sufficient* tools for achieving robust operation. However, this design choice often leads to over-utilization of the available resources as it might not be necessary to execute a pessimistic control law at each time instant. For industrial applications, especially in process control industry where economic concerns are directly effecting the operation decisions, the pessimistic control methods are in general rejected and robustness is achieved in an ad-hoc manner [17]. In recent years, a huge effort has been put in developing computationally efficient (or tractable) and less pessimistic (or adjustable) robust optimization tools that have parameter ambiguity and stochastic uncertainties within the formulation of the optimization (equivalently MPC) problems [18].

It is important to distinguish three different robustness aspects of MPC algorithms in the way of treating uncertain effects,

(1) robust feasibility,
(2) robust stability,
(3) robust (closed-loop) performance.

The robust feasibility is about the constraint satisfaction in the face of uncertainty, while the robust stability is tracked via the cost function through Lyapunov based stability arguments. We have a considerable understanding on robust constraint satisfaction or robust stability while the interplay between the uncertainty and the closed-loop performance is yet to be rigorously analyzed. Although there exist some methods to synthesize predictive controllers that operate in a computationally acceptable way [19], many of the current robust MPC methods lead to computationally challenging optimization problems, while causing unacceptable levels of performance deterioration. The performance deterioration, or even the total absence of performance, due to overly conservative methods is causing a gap between academic works and industrial implementations. High performance is achieved if the uncertain effects are compensated when it is required, while robustness requirements demand to act in a pre-emptive manner. Hence incorporating *only the necessary* uncertain process predictions into the control action by incorporating risk management techniques is of great interest for predictive control applications.

Combining robust control and predictive control regarding the robust constraint satisfaction, stability and performance aspects with quantitative guarantees is still an open problem. There are a multitude of techniques, detailed in the next sections, to reshape robust MPC (RMPC) (or similarly stochastic MPC (SMPC)) problems. The main dilemma is due to the open-loop nature of predictions, leading to loss of incorporation of *future* uncertainty into the control actions. Dynamic programming (DP) techniques provide a way out of this problem, however the *curse of dimensionality*, specifically for moderate or large scale systems or uncertainty spaces, drastically effects the computational aspects, see [20].

Another important point regarding the industrial acceptance of RMPC algorithms is the computational aspect. It is a requirement that RMPC problems should be consisting of relatively simple

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[1] Here we do not consider the difficult questions of how and at which complexity level the process model should be constructed. We refer the interested reader to [12,13] as introductory discussion on modeling uncertain behaviour.