Robust Model Predictive Control via Scenario Optimization

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Abstract – This paper discusses a novel probabilistic approach for the design of robust model predictive control (MPC) laws for discrete-time linear systems affected by parametric uncertainty and additive disturbances. The proposed technique is based on the iterated solution, at each step, of a finite-horizon optimal control problem (FHOCP) that takes into account a suitable number of randomly extracted scenarios of uncertainty and disturbances, followed by a specific command selection rule implemented in a receding horizon fashion. The scenario FHOCP is always convex, also when the uncertain parameters and disturbance belong to non-convex sets, and irrespective of how the model uncertainty influences the system’s matrices. Moreover, the computational complexity of the proposed approach does not depend on the uncertainty/disturbance dimensions, and scales quadratically with the control horizon. The main result in this paper is related to the analysis of the closed loop system under receding-horizon implementation of the scenario FHOCP, and essentially states that the devised control law guarantees constraint satisfaction at each step with some a-priori assigned probability \(p\), while the system’s state reaches the target set either asymptotically, or in finite time with probability at least \(p\). The proposed method may be a valid alternative when other existing techniques, either deterministic or stochastic, are not directly usable due to excessive conservatism or to numerical intractability caused by lack of convexity of the robust or chance-constrained optimization problem.

1 Introduction

In Model Predictive Control (MPC), at each sampling time \(t\), a plant’s control input \(u_t \in \mathbb{R}^m\) is computed by solving a constrained finite horizon optimal control problem (FHOCP), according to a receding horizon (RH) strategy, see, e.g., [1]. MPC has received an ever-increasing attention in the last decades, mainly due to the possibility of taking into account input and state constraints explicitly in the control design. The study of robust MPC approaches, able to guarantee stability and constraint satisfaction also in the presence of uncertainty/disturbances, is still a very active research area. For the case of linear time invariant (LTI) discrete time models, an extensive literature has been developed, considering the presence of either model uncertainty or external disturbances, see, e.g., [2]-[12]. Most of the existing approaches are deterministic and aim to optimize a worst-case performance index, while enforcing constraints for all possible outcomes of the uncertainty [2]-[4] or disturbance [5]-[8]. These techniques guarantee that the designed control law is able to cope with the considered uncertainty. However, they rely on the assumption of convexity of the optimization problem, not only with respect to the control input, but also...
with respect to the uncertain parameters and disturbances. Moreover, the computational complexity of deterministic approaches typically grows with the complexity of the model set. In a recent and active research direction, stochastic MPC techniques have also been studied, see, e.g., [9]-[12] and the references therein. Stochastic MPC techniques exploit some known statistical description of the uncertain parameters and/or of the disturbance (e.g., the probability distribution, or the first and second moments), yet they still employ deterministic algorithms and, in order to maintain tractability of the optimization problem, they typically assume that the system matrices are either perfectly known, or they have a particular structure that preserves convexity.

We propose here a new randomized method for robust MPC design, which is able to deal with both model uncertainty and additive disturbances. Similar to stochastic MPC techniques, we exploit information on the statistics of the uncertain parameters and disturbances. However, we do not assume convexity or even connectedness of the model set or of the disturbance set. Still, the optimization problem in our approach is always convex, and the control law is able to robustly enforce constraints and trajectory convergence, with a probability higher than a user-defined value \( p \). Furthermore, for a given value of \( p \), the computational complexity of our approach is completely independent of the complexity of the model set. The key point enabling to achieve these features is a shift of paradigm, from a deterministic algorithm to a randomized one, i.e., an algorithm that relies on random choices in the course of its execution (see, e.g., [13]). Indeed, a key step in our main algorithm (Algorithm 4.1) is the solution of a scenario FHOCP, in which we do not consider all possible outcomes of uncertainty and disturbances, but only a finite number \( M \) of randomly chosen instances of them, named the “scenarios.” A randomized approach for MPC has been studied also in [14]-[15], by using a Monte Carlo technique. However, Monte Carlo approaches may be very computationally demanding and can not handle in a straightforward way the presence of state constraints. Randomization has been used also in [10], in the context of chance-constrained MPC. However, in [10] there is no guideline on how to choose \( M \) in order to have the guarantee that the probability of success is at least \( p \) (which is instead one of the features of the present approach) and, moreover, the resulting optimization problem is a mixed-integer linear program. On the contrary, the approach proposed here, named MPCS (MPC via Scenario optimization), exploits relatively recent results in Random Convex Programming (RCP, see [17]-[20]) to provide an explicit link between \( M \) and \( p \). Moreover, we introduce a slack variable, the “constraint violation,” which renders the scenario FHOCP always feasible, and that can be used to monitor the extent of the (possible) violation of the involved constraints. Further, we show how scenario optimization can be embedded in a receding horizon scheme, in order to provide a feedback controller that gives probabilistic guarantees of robust stability and constraint satisfaction. The approach here proposed shall be particularly interesting in all those cases where the assumptions underpinning the existing deterministic or stochastic approaches for robust MPC are not met; for example, when the dependence of the system matrices on the uncertain parameters is not affine.

### 2 Problem formulation

Consider the following uncertain, discrete time LTI model:

\[
x_{t+1} = A(\theta)x_t + B(\theta)u_t + B_\gamma(\theta)\gamma_t
\]

where \( t \in \mathbb{Z} \) is the discrete time variable, \( x_t \in \mathbb{R}^n \) is the system state, \( u_t \in \mathbb{R}^m \) is the control input, \( \gamma_t \in \Gamma \subseteq \mathbb{R}^m \) is an unmeasured disturbance vector, \( \theta \in \Theta \subseteq \mathbb{R}^g \) is the vector of uncertain parameters, and \( A(\theta), B(\theta), B_\gamma(\theta) \) are matrices of suitable dimensions. Let us consider the following assumptions:

**Assumption 1 (Uncertainty description)** The sets \( \Gamma \) and \( \Sigma = \{A(\theta), B(\theta), B_\gamma(\theta) : \theta \in \Theta\} \) are bounded. We assume \( \gamma_t \) and \( \theta \) to have stochastic nature, and we let \( \mathbb{P}_\theta \) denote the probability measure on \( \Theta \), and \( \mathbb{P}_\gamma \) the probability measure on \( \Gamma \). Variables \( \theta \) and \( \gamma_t \) are independent. Moreover, \( \gamma = \{\gamma_0, \gamma_1, \ldots\} \) is an independent identically distributed (i.i.d.) sequence and we let \( \mathbb{P}_\gamma^\infty \) denote the probability measure on this sequence.

**Assumption 2 (Robust stabilizability)** The pair \( A(\theta), B(\theta) \) is stabilizable for any \( \theta \in \Theta \).
The control problem is to regulate the system state to a neighborhood of the origin, subject to (possibly uncertain) input and state constraints \( x_t \in X(\theta), u_t \in U(\theta), \forall t \). The next assumption characterizes the constraint sets.

**Assumption 3** (State and input constraints) For any \( \theta \in \Theta \), the sets \( X(\theta) \subseteq \mathbb{R}^n \) and \( U(\theta) \subseteq \mathbb{R}^m \) are convex; they contain the origin in their interiors and they are representable by: \( X(\theta) = \{ x \in \mathbb{R}^n : f_X(x, \theta) \leq 0 \} \), \( U(\theta) = \{ u \in \mathbb{R}^m : f_U(u, \theta) \leq 0 \} \), where \( \leq \) denotes element-wise inequalities, each entry of the functions \( f_X : \mathbb{R}^n \times \Theta \rightarrow \mathbb{R}, f_U : \mathbb{R}^m \times \Theta \rightarrow \mathbb{R} \) is convex in \( x \) and \( u \), respectively, and \( r, q \) are suitable integers.

The parameter \( \theta \) has been included in the constraints to account for practical applications where, for example, a convex function of the states (e.g., energy, load) has to be limited below some threshold, and some parameter in the function or the threshold itself depend on uncertain physical quantities (e.g., maximal energy, breaking load). Assumptions 1 and 3 are quite mild, since \( \Theta \) may be unbounded and of any form, no assumption on \( \Sigma, \Gamma \) is made except for boundedness, no restrictions on how the parameter \( \theta \) influences matrices \( A(\theta), B(\theta), B_{\gamma}(\theta) \) are imposed, as long as the system is stabilizable, and finally no assumption on the shape of the convex sets \( X(\theta), U(\theta) \) (e.g., polytopic, ellipsoidal, ...) for given \( \theta \in \Theta \) is made. Mixed constraints of the form \( (x, u) \in X_U(\theta) \), where \( X_U(\theta) \subseteq \mathbb{R}^n \times \mathbb{R}^m \) is a convex set, are not considered here for simplicity, but they can be straightforwardly included in our problem settings. Due to the presence of the generally non-zero unmeasured disturbance \( \gamma_t \), regulation of the system state to the equilibrium \( x = 0, u = 0 \) can not be attained. Rather, we can require regulation to a neighborhood of the origin, described by a terminal set, which is robustly positively invariant under a terminal control law.

**Assumption 4** (Terminal set and terminal control law) A convex set \( X_f \) and a linear terminal control law \( u = K_f x, K_f \in \mathbb{R}^{m \times n} \), exist for system (1), such that \( X_f = \{ x : f_X(x, \theta) \leq 0 \} \); \( A(\theta)x + B(\theta)K_f x + B_{\gamma}(\theta)\gamma \in X_f, \forall \theta \in \Theta, \forall \gamma \in \Gamma, \forall x \in X_f \); finally \( f_X(x, \theta) \leq 0, f_U(K_f x, \theta) \leq 0, \forall \theta \in \Theta, \forall x \in X_f \), where \( f_X, f_U : \mathbb{R}^n \rightarrow \mathbb{R}^t \) has convex components, and \( l \) is a suitable integer.

A possible method for constructing a terminal set and a terminal control law satisfying Assumption 4 is to apply results in quadratic stability and rejection of bounded disturbances for uncertain LTI systems, see, e.g., [21][22] and the references therein. Moreover, there is a number of contributions in the literature concerned with the computation of approximations of the (minimal) robust positively invariant terminal set \( X_f \), see e.g. [23][24] and the references therein. In the rest of this note, we parameterize the control input as:

\[
    u_t = K_f x_t + v_t,
\]

where \( K_f \) is the terminal control law of Assumption 4 (which is assumed to be known and given), and \( v_t \) is a control correction to be designed. Plugging (2) into (1), we obtain the discrete-time model

\[
    x_{t+1} = A_{cl}(\theta)x_t + B(\theta)v_t + B_{\gamma}(\theta)\gamma_t,
\]

with \( A_{cl}(\theta) = A(\theta) + B(\theta)K_f \), which will be the basis of our developments.

### 3 The Scenario-based Finite-Horizon Optimal Control Problem

Suppose that, at a given time instant \( t \), the state \( x_t \) of system (3) is observed. We consider the problem of determining a corrective control sequence on a horizon of \( N \) instants forward in time. To this end, we build a randomized finite-horizon optimal control problem (FHOCP), as described next. Let \( N \) be the chosen horizon length, and let \( v_{j|t}, j = 0, 1, \ldots, N-1 \), be the \( N \) predicted control corrections to be applied to (3), from \( t \) to \( t+N-1 \), given the knowledge of the state at time \( t \). From (2), the corresponding predicted control input sequence is \( u_{j|t} = K_f x_{j|t} + v_{j|t}, j = 0, 1, \ldots, N-1 \). By using model (3), we thus obtain the predicted values of the states as linear functions of the current state \( x_t \), of the predicted (to-be-determined) control sequence \( V^t = [v_{0|t} \cdots v_{N-1|t}]^T \in \mathbb{R}^{Nm} \), and of the disturbance sequence \( \gamma \):

\[
    x_{j|t} = A_{cl}(\theta)x_t + \Phi_f(\theta)V_t + Y_f(\theta)\gamma, \quad j = 1, \ldots, N,
\]
where \( \Phi_j(\theta), \Upsilon_j(\theta) \) are suitable functions of the model matrices, \( A_{cl}(\theta), B(\theta) \) and \( B_j(\theta) \). However, the predictions obtained via model (7) are uncertain, since they depend on \( \theta \) and on \( \gamma \). In our approach, we deal with this issue by considering a discrete set of predicted state and input trajectories, obtained for a number \( M \) of randomly extracted scenarios of \( \theta \) and \( \gamma \) at time \( t \). More precisely, let us collect these random parameters in \( \delta = (\theta, \gamma), \delta \in \Delta = \Theta \times \Gamma^\infty \). As a consequence of Assumption 1 we have that \( \delta \) has a probability measure that we denote with \( \mathbb{P} \), which is the product measure of \( \mathbb{P}_\theta \) and the measure \( \mathbb{P}_\gamma^\infty \) on \( \gamma: \mathbb{P} = \mathbb{P}_\theta \times \mathbb{P}_\gamma^\infty \). Consider then \( M \) independent extractions \( \delta^{(1)}_t, \ldots, \delta^{(M)}_t \) of \( \delta \), constituting the scenarios, where each scenario has the probability distribution \( \mathbb{P} \), and let \( \omega_t = (\delta^{(1)}_t, \ldots, \delta^{(M)}_t) \) denote the “multisample” of scenario extractions at time \( t \). The probability distribution on \( \omega_t \) is given by \( \mathbb{P}^M \).

Based on the random scenarios, we obtain \( M \) different state and input predictions from (4), namely, for \( i = 1, \ldots, M \),

\[
\begin{align*}
x^{(i)}_{0|t} &= x_t, \\
x^{(i)}_{j|t} &= A_{cl}^j(\theta^{(i)}_t)x_t + \Phi_j(\theta^{(i)}_t)\nu_t + \Upsilon_j(\theta^{(i)}_t)\gamma^{(i)}_t, \\
v^{(i)}_{j|t} &= K_f x^{(i)}_{j|t} + v_{j|t}, \quad j = 0, \ldots, N - 1,
\end{align*}
\]

(5)

where \( (\theta^{(i)}_t, \gamma^{(i)}_t) = \delta^{(i)}_t \). Let us now introduce the following cost function:

\[
J(x_t, \omega_t; \nu_t) \doteq \max_{i = 1, \ldots, M} \left( \sum_{j=0}^{N-1} d(x^{(i)}_{j|t}, X_f) + \sum_{j=0}^{N-1} v^{(i)}_{j|t}^T \Lambda v_{j|t} \right),
\]

(6)

where \( d(x, X_f) \) is the distance between \( x \) and the terminal set \( X_f \), computed in some norm \( \| \cdot \| \) : \( d(x, X_f) \doteq \min_{y \in X_f} \| x - y \| \), and \( \Lambda = \Lambda^1 > 0 \) is a weighting matrix chosen by the control designer. In the following, with a slight abuse of notation, we indicate the state and input constraint sets as \( X(\delta) \), \( U(\delta) \), respectively, and the related convex functions in Assumption 3 as \( f_X(x, \delta), f_U(u, \delta) \). Moreover, we transform the hard constraints of Assumption 3 into soft ones, by introducing a slack variable \( q_t \in \mathbb{R}, q_t \geq 0 \). Then, the scenario-based FHOCP is a random convex program defined as follows:

\[
\mathcal{P}(x_t, \omega_t): \min_{\nu_t, z_t, q_t} \ z_t + \alpha q_t
\]

subject to

\[
\begin{align*}
J(x_t, \omega_t; \nu_t) &\leq z_t, \quad (7b) \\
f_X(x^{(i)}_{j|t}, \delta^{(i)}_t) - \nu^{(i)}_t \leq 0; \quad j = 1, \ldots, N - 1, \quad i = 1, \ldots, M, \quad (7c) \\
f_U(v^{(i)}_{j|t}, \delta^{(i)}_t) - \nu^{(i)}_t \leq 0; \quad j = 0, \ldots, N - 1, \quad i = 1, \ldots, M, \quad (7d) \\
f_X(x^{(i)}_{t+N|t}) - \nu^{(i)}_t \leq 0; \quad i = 1, \ldots, M, \quad (7e) \\
q_t &\geq 0 \quad (7f)
\end{align*}
\]

In (7a), the weighting scalar \( \alpha > 0 \) is chosen by the control designer, and 1 denotes a column vector of appropriate length, containing all ones. We denote with \( \nu_t^* = \{ \nu^{(i)}_0, \ldots, \nu^{(i)}_{N-1} \} \), \( z_t^* = \{ z_t^* \} \) and \( q_t^* = \{ q_t^* \} \) an optimal solution to problem (7).

**Remark 3.1 (Worst-case cost and constraint violation)** Due to the presence of constraint (7b), the value \( z_t^* \) is an upper bound of the worst case cost with respect to all the \( M \) extracted scenarios. We thus refer to \( z_t^* \) as the “worst-case cost.” Moreover, we note that the use of the soft constraints (7c) - (7f) imply that problem (7) is always feasible. In particular, by using a sufficiently high value of \( \alpha \) (e.g. \( 10^4 \) times higher than the typical value of \( z_t^* \)), the optimal value of \( q_t^* \) turns out to be negligible whenever the problem with hard constraints (i.e., with \( q_t \) set a priori to zero) is feasible. Contrary, when the problem with hard constraints is not feasible, the variable \( q_t^* \) provides an indication on “how much” some of the constraints are violated. For this reason, we refer to \( q_t^* \) as the “constraint violation” level. Finally, we note that there is no constraint violation in (7b), i.e. \( z_t^* \) is always greater than all the cost functions corresponding to the sampled scenarios, and in particular it is always an upper bound of the distance between the state \( x_t \) and the terminal set \( X_f \) (see (5)). This feature is important for our convergence result in Section 4. \( \blacksquare \)
Remark 3.2 (Choice of cost function and input parameterization) Prediction of the state trajectories in a closed loop fashion is quite common in the context of robust MPC, see e.g. \cite{14} \cite{21}. In particular, we adopt here the input parameterization (2), and we optimize over the control corrections $v_{ijt}$, $j = 0, \ldots, N - 1$, i.e. over $N$ in decision variables. Moreover, we chose as stage cost the distance between the state and the terminal set, plus a quadratic penalty on the control correction. Indeed, these choices of control parameterization and cost function are not meant to be the sole possibility, neither the optimal, for the proposed approach. Generalization to other kinds of input parameterization (e.g. disturbance-feedback \cite{14} \cite{21}) and cost function (like a standard quadratic stage cost) can be done with some technical modifications in the proofs reported in this note.

The optimization problem $\mathcal{P}(x_t, \omega_t)$ can be rewritten in a more compact standard form. By collecting the optimization variables $(V_t, z_t, q_t)$ in vector $s_t \in \mathbb{R}^{mN+2}$, the cost can be expressed as $z_t + \alpha q_t = c^T s_t$, where $c = [0, \ldots, 0, 1, 0]^T$. Moreover, it can be noted that, for any fixed value of $\delta_t$, due to linearity of \cite{5}, the constraints (71)-(74) are convex in the decision variable $s_t$ and in the state $x_t$. Finally, these constraints can be formally expressed compactly as $h(s_t, x_t, \delta_t) \leq 0$, for all $i = 1, \ldots, M$, where $h : \mathbb{R}^{mN+2} \times \mathbb{R}^n \times \Delta \to \mathbb{R}$ is defined as $h(s_t, x_t, \delta_t) = \max \left\{ \sum_{j=0}^{N-1} \left( f_X(x_t^{(i)}|x_{ijt}), \delta_t^{(i)} - 1\beta, f_U(v_{ijt}^{(i)}), \delta_t^{(i)} - 1\beta \right) \right\}$. Notice that $h(s_t, x_t, \delta_t)$ is convex in both $s_t$ and $x_t$, since it is the point-wise maximum of convex functions. The scenario FHOCP can hence be rewritten as

$$\mathcal{P}(x_t, \omega_t) : \min_{s_t} c^T s_t$$

subject to: $h(s_t, x_t, \delta_t) \leq 0$, $i = 1, \ldots, M$.

We denote with $s^*_t(x_t, \omega_t) = (V^*_t, z^*_t, q^*_t)$ an optimal solution of $\mathcal{P}(x_t, \omega_t)$. Notice that, due to the way it has been defined, problem $\mathcal{P}(x_t, \omega_t)$ is always feasible. We further assume that this problem always attains a unique optimal solution.

### 3.1 Properties of the scenario FHOCP

We now consider the following problem: suppose that, given the state $x_t$, we solve problem $\mathcal{P}(x_t, \omega_t)$. Then, we ask what is the probability that the computed optimal control sequence $V^*_t(x_t, \omega_t)$ is able to satisfy all state and input constraints over the chosen horizon, and to drive the state trajectory to the terminal set at the end of the horizon, within the computed optimal constraint violation $q^*_t$. Formally, this is the probability (with respect to $\delta$) with which $h(s^*_t, x_t, \delta) \leq 0$, where we notice that $h$ is now evaluated at the optimal scenario solution $s^*_t$; the state and input trajectories that enter the definition of $h$ are the “actual,” uncertain, ones, obtained from model \cite{5} at a random $\delta = (\theta, \gamma)$. So, we define the reliability $R$ of the scenario-FHOCP as

$$R \doteq \mathbb{P}\{\delta : h(s^*_t, x_t, \delta) \leq 0\}.$$ 

Notice that $R \in [0, 1]$ is itself a random variable, since it depends on $s^*_t$, which in turn depends on the random multi-extraction of the scenarios $\omega_t$, hence $R = R(\omega_t)$. Indeed, for some extractions $\omega_t$ the reliability can be good (close to one), and for other extractions it can be bad. It is therefore critical to assess the a-priori likelihood of these two situations, that is to precisely quantify bounds on the probability of the “bad” event where $\{R < p\}$, being $p$ some a-priori assigned level or desired reliability. To this purpose, we exploit the fact that problem $\mathcal{P}(x_t, \omega_t)$ belongs to the class of so-called Random Convex Programs (RCP) (see, e.g., \cite{17} \cite{20}) and, in particular, the result in Theorem 1 of \cite{19}, concerned with feasible random convex programs, applies to our context. The following key result directly follows from Theorem 1 of \cite{19}, see also Theorem 3.3 in \cite{20}.

**Theorem 3.1** Let $d = mN + 2$ be the number of decision variables in problem $\mathcal{P}(x_t, \omega_t)$, let $p \in (0, 1)$ be a given desired reliability level, let $\beta \in (0, 1)$ be a given small probability level (say, $\beta = 10^{-9}$), and let $M$ be an integer such that

$$\Phi(p, d, M) \leq \beta,$$ 

(9)
with \( \Phi(p,d,M) = \sum_{j=0}^{d-1} \binom{M}{j} (1-p)^j p^{M-j} \). Then, it holds that

\[
\mathbb{P}^M \{ \omega_t : R(\omega_t) \geq p \} \geq 1 - \beta. \tag{10}
\]

**Remark 3.3** (Number of scenarios and “certainty equivalence”) The practical importance of the result in Theorem 3.1 stems from the fact that the number \( M \) of scenarios necessary to fulfill condition (9) grows mildly with the inverse of \( \beta \). More precisely, Corollary 5.1 in [20] states that condition (9) is implied by \( M \geq \frac{1}{2p} (\ln \beta^{-1} + d) \), thus \( M \) grows at most logarithmically with \( \beta^{-1} \) (tighter values of \( \beta \) for given \( \beta \) and \( p \) can be obtained by inverting numerically (10)). This means in turn that the parameter \( \beta \) may be fixed by the designer to a very low level, say \( \beta = 10^{-9} \), or even \( \beta = 10^{-12} \), and still the number \( M \) of scenarios necessary to guarantee (10) remains manageable. The parameter \( \beta \) hence measures the probability of the unfortunate event in which the optimal solution has reliability smaller than the desired level \( p \). If the likelihood of such an event is bounded a priori by an extremely low value, such as \( \beta = 10^{-12} \), then we may safely say that, to all practical engineering purposes, the event \( \{ R(\omega_t) \geq p \} \) is the “certain” event. In other words, the possibility that \( \{ R(\omega_t) \geq p \} \) is not satisfied by the scenario problem is so remote that, before having any concern about it, the designer should better verify the validity of many other assumptions and approximations in the model. Such a “certainty equivalence” principle, which will be adopted henceforth in this paper, essentially eliminates from consideration the “outer” probability level in (10), and states with practical certainty (the expression “with practical certainty” shall be used in the rest of this note as a synonym of “with probability larger than \( 1 - \beta \),” where \( \beta > 0 \) is some extremely small value) that \( \{ R(\omega_t) \geq p \} \) holds. This simplifies greatly the practical application of scenario techniques, and makes the whole approach more clear and understandable by both theoreticians and control practitioners.

The properties of the scenario FHOCP are resumed in the following proposition.

**Proposition 3.1** (Finite horizon robustness) Given the state \( x_t \) of system (3) at time \( t \), consider the scenario problem \( P(x_t, \omega_t) \) as an instrument to derive a finite-horizon control sequence \( v_t^* = \{ v_{0t}^*, \ldots, v_{N-1t}^* \} \) to be applied to the system (3) at the subsequent instants \( t, t+1, \ldots, t+N-1 \). Let the number \( M \) of scenarios in problem \( P(x_t, \omega_t) \) be chosen so to satisfy (9) for given reliability level \( p \in (0,1) \) and very small \( \beta \in (0,1) \). Then, with practical certainty it holds that the computed control sequence:

a) steers the state of system (3) to the terminal set \( X_f \) in \( N \) steps with probability at least \( p \) and constraint violation \( q_{t,j}^* \), i.e.: \( \mathbb{P} \{ \delta : f_X(x_t, x_{t+j}, \delta) - 1 q_{t,j}^* \leq 0, \forall j \in [1, N] \} \geq p \);

b) satisfies all state constraints with probability at least \( p \) and constraint violation \( q_{t,j}^* \), i.e.: \( \mathbb{P} \{ \delta : f_X(x_t, x_{t+j}, \delta) - 1 q_{t,j}^* \leq 0, \forall j \in [1, N] \} \geq p \);

c) satisfies all input constraints with probability at least \( p \) and constraint violation \( q_{t,j}^* \), i.e.: \( \mathbb{P} \{ \delta : f_U(u_{t+j}, \delta) - 1 q_{t,j}^* \leq 0, \forall j \in [0, N-1] \} \geq p \).

The proof of this result follows immediately from Theorem 5.1, eq. (10) states that, with practical certainty, the optimal solution \( s_t^* \) of the scenario problem satisfies \( h(s_t^*, x_t, \delta) \leq 0 \) with probability at least \( p \), which indeed implies that points a)-c) in the corollary hold.

**Remark 3.4** (Relationship with deterministic approaches) In a deterministic approach to robust MPC, a problem similar to (7) has to be solved for all possible values of \( \delta \in \Delta \). When the problem is convex with respect to \( \delta \) (which happens, for instance, when the uncertain matrices and/or the additive disturbance belong to polytopes [2] [7]), deterministically robust approaches are indeed well-established and shall be preferred to the scenario approach, especially if deterministic robustness is critical in the considered application. In all other cases, deterministic approaches are generally intractable, unless the problem is manipulated so to satisfy convexity assumptions, at the cost of higher conservativeness and reduced feasibility. In these situations, the scenario approach proposed here is a viable alternative to deterministic techniques, since it is always convex and it can be efficiently solved also with a large number of samples, while still giving probabilistic guarantees on the robustness of the solution, as it will be shown in the example section. Moreover, we note that, if a sufficiently high weight \( \alpha \) is used in the objective (see
Remark 3.1: when the scenario problem typically returns a negligible optimal constraint violation \( q^*_t \), whenever the problem would be feasible with \( q_t \) set to zero. Furthermore, since the scenario FHOCP has only a subset of the constraints of a corresponding deterministically robust FHOCP, the violation level \( q^*_t \) of the scenario problem will always be lower than the violation level of the deterministic version of the same problem (and this fact holds independently of whether the deterministic problem can be solved numerically or not). In any case, the value of \( q^*_t \) gives an indication on the extent of the violation of the involved constraints, which can be used, e.g., to implement supervisory control strategies and recovery actions.

The remaining part of this note is devoted to analyzing what happens when a scenario FHOCP is solved repeatedly in time and used to control the plant in a receding-horizon fashion. In a receding-horizon approach, which is the key feature of MPC, only the first control correction in the optimal sequence \( \mathcal{V}_t \) is applied at time \( t \), and then the FHOCP is solved again at time \( t + 1 \), by exploiting the knowledge of the state \( x_{t+1} \), etc. In the next section, we propose a technique for incorporating the scenario FHOCP into a suitable receding-horizon scheme, and we derive probabilistic guarantees of asymptotic convergence and constraint satisfaction for the resulting closed-loop system.

4 MPC scheme based on Scenario optimization

We here introduce a receding-horizon implementation of a control algorithm based on the scenario FHOCP, as described next. The notation is set as follows: “\( z^* \)” variables, such as \( z^*_t, q^*_t, V_t^* = \{v_{0|t}^*, \ldots, v_{N-1|t}^* \} \), denote the optimal solution of the scenario optimization problem \( \mathcal{P}(x_t, \omega_t) \) at time \( t \), given \( x_t \); “\( \omega^* \)” variables, \( z_t, q_t, \mathcal{V}_t \), denote, respectively, two scalar values and a sequence of \( N \) vectors of dimension \( m \), as defined in the algorithm below; finally plain variables, \( z_t, q_t, \mathcal{V}_t \), denote the running values of the variables \( z, q \) and of the sequence \( V = \{v_{0|t}, \ldots, v_{N-1|t} \} \) in the algorithm. The first entry in \( \mathcal{V}_t \), namely \( v_{0|t} \), is the actual control correction that is applied to the system \( 2 \) at time \( t \). The subsequence composed by the last \( N - 1 \) elements of \( \mathcal{V}_t \) is denoted with \( v_{1:N-1|t} \). We are now in position to describe the algorithm for MPC based on Scenario optimization (MPCS).

Algorithm 4.1 (MPCS algorithm)

(\textbf{Initialization}) Choose a desired reliability level \( p \in (0,1) \) and “certainty equivalence” level \( \beta \in (0,1) \) (say, \( \beta = 10^{-9} \), or \( \beta = 10^{-12} \)). Let \( M \) be an integer satisfying \( \{M\} \) below for the meaning of \( \epsilon \) and for guidelines on its choice. Given an initial state \( x_0 \), extract \( \omega_0 \) according to \( \mathbb{P}^M \), solve problem \( \mathcal{P}_M(x_0, \omega_0) \) and obtain the optimal control sequence \( V_0^* = \{v_{0|0}^*, v_{1|0}^*, \ldots, v_{N-1|0}^* \} \), and the optimal objective \( z^*_0 \) and constraint violation \( q^*_0 \). Set \( z_0 = z^*_0, q_0 = q^*_0, V_0 = V_0^* \), and apply to the system the control action \( u_0 = K_f x_0 + v_{0|0} \).

1) Let \( t := t + 1 \), observe \( x_t \), and set \( \mathcal{V}_t = \{v_{1|t-1}, \ldots, v_{N-1|t-1}, 0\} = \{v_{1:N-1|t-1}, 0\} \),\n\[
\tilde{z}_t = \max(0, z_t - d(x_{t-1}, X_f)), \quad \tilde{q}_t = q_{t-1};
\]
2) Extract the multi-sample \( \omega_t \) according to \( \mathbb{P}^M \), and solve problem \( \mathcal{P}_M(x_t, \omega_t) \). Let \( (V_t^*, z_t^*, q_t^*) \) be the obtained optimal solution.

3) Evaluate the following collectively exhaustive and mutually exclusive cases:

3.a) If \( z_t^* > (z_{t-1} - \epsilon d(x_{t-1}, X_f)) \) and \( \tilde{z}_t < d(x_{t-1}, X_f) \), then set \( \mathcal{V}_t = \mathcal{V}_t^*; \quad z_t = 0; \quad q_t = \tilde{q}_t; \)
3.b) If \( z_t^* > (z_{t-1} - \epsilon d(x_{t-1}, X_f)) \) and \( \tilde{z}_t \geq d(x_{t-1}, X_f) \), then set \( \mathcal{V}_t = \mathcal{V}_t^*; \quad z_t = \tilde{z}_t; \quad q_t = \tilde{q}_t; \)
3.c) If \( z_t^* \leq (z_{t-1} - \epsilon d(x_{t-1}, X_f)) \), then set \( \mathcal{V}_t = \mathcal{V}_t^*; \quad z_t = z_t^*; \quad q_t = q_t^*; \)
4) Apply the control input \( u_t = K_f x_t + v_{0|t} \), then go to 1).

Remark 4.1 The inequality \( z_t^* \leq (z_{t-1} - \epsilon d(x_{t-1}, X_f)) \), checked at step 3) of the MPCS algorithm, can be interpreted as a verification of a required minimum improvement, in terms of worst-case cost, achieved by the newly computed optimal solution \( (V_t^*, z_t^*, q_t^*) \) of the scenario problem at time step \( t \), with respect to the previous step. The user-defined parameter \( \epsilon \in (0,1] \) influences such a requirement: the closer the value of \( \epsilon \) is set to 0, the more likely it is that case \( z_t^* \leq (z_{t-1} - \epsilon d(x_{t-1}, X_f)) \) is met, so that the MPCS algorithm relies, at each time step, on the newly computed optimal solution. Vice-versa, the closer is the value of \( \epsilon \) to 1, the more likely it is that the complementary condition \( z_t^* > (z_{t-1} - \epsilon d(x_{t-1}, X_f)) \) is detected, so that the MPCS algorithm employs the previously computed solution.
The next results is concerned with the guaranteed properties, in terms of constraint satisfaction and convergence to the terminal set, of the closed loop system obtained by applying Algorithm 4.1.

**Theorem 4.1 (Properties of Scenario MPC)** Let Assumptions 1-4 be satisfied and let \( p \in (0, 1) \) be a chosen reliability level. Let \( v_{0:t}, t = 0, 1, \ldots \) denote the sequence of control actions produced by Algorithm 4.1 and consider the closed loop system obtained by applying to (1) the control law \( u_t = K_f x_t + v_{0:t} \). Then:

(a) With practical certainty, at all time steps \( t = 0, 1, \ldots \), the probability that the state and input constraints are satisfied with constraint violation \( q_t \) is at least \( p \), that is \( P(\delta : f_X(x_{t+1}, \delta) - 1q_t \leq 0 \cap f_V(u_t, \delta) - 1q_t \leq 0) \geq p, \quad t = 0, 1, \ldots \).

(b) Algorithm 4.1 either: (i) makes the state trajectory converge asymptotically to the terminal set, i.e. \( \lim_{t \to \infty} d(x_t, X_f) = 0 \), or (ii) there exists a finite time \( t^* \) such that, with practical certainty, the control sequence \( \{v_{0:t^*}, v_{0:t^*+1}, \ldots, v_{0:|\tau + N - 1|}\} \) drives the state of the closed-loop system to the terminal set at time \( t^* + N - 1 \), with probability at least \( p \) and constraint violation \( q_{t^*} \).

**Proof of statement (a).** At time \( t = 0 \), Proposition 3.1 guarantees with practical certainty that the first control correction satisfies the constraints on \( u_0 \) and \( x_1 \) with probability no less than \( p \) and constraint violation \( q_t = q_1^* \). At any generic time step \( t \geq 1 \), the variables \((\bar{V}_t, \bar{z}_t, \bar{q}_t)\) are computed. Then, two cases may occur. If \( z_t^* \leq (z_{t-1} - \varepsilon d(x_{t-1}, X_f)) \), then case 3.c) is detected, and the first element \( v_{0:t}^* \) of the optimal sequence \( V_t^* \) is applied to the system. Being this sequence the solution of a scenario optimization problem, with practical certainty the probability of satisfying state and input constraints is no less than \( p \), with constraint violation \( q_t = q_t^* \). If, on the other hand, \( z_t^* > (z_{t-1} - \varepsilon d(x_{t-1}, X_f)) \), then we are either in case 3.a) or 3.b), and in both cases the element \( v_{k[t-1]}^* \), for some \( k \in [1, N - 1] \), is applied to the system. Being this value part of the solution sequence \( V_{t-k}^* \), with corresponding constraint violation \( q_{t-k}^* \), again the probability of satisfying state and input constraints is no less than \( p \), with constraint violation \( q_t = q_t^* \). Thus, in any case, with practical certainty, at each time step the MPC algorithm guarantees satisfaction of state and input constraints with probability no less than \( p \) and constraint violation \( q_t \).

**Proof of statement (b).** Each run of Algorithm 4.1 may have one of two possible behaviors, depending on whether or not there exists a finite time \( t > 0 \) such that \( z_t^* > (z_{t-1} - \varepsilon d(x_{t-1}, X_f)) \) and \( \bar{z}_t < d(x_t, X_f) \), that is, whether or not the situation in step 3.a is ever satisfied. We then name \( \tilde{A} \) the situation when condition in step 3.a is met at some finite time \( t > 0 \), and \( \tilde{A} \) the complementary situation when this condition is not satisfied at any finite time, that is when \( z_t^* \leq (z_{t-1} - \varepsilon d(x_{t-1}, X_f)) \) or \( \bar{z}_t \geq d(x_t, X_f) \) holds for all \( t > 0 \).

1. Let us first consider the situation of case \( \tilde{A} \). Consider a generic time \( t \). At step 3) of the MPC algorithm, if \( z_t^* > (z_{t-1} - \varepsilon d(x_{t-1}, X_f)) \), then, since it is assumed that we are in situation \( \tilde{A} \), it must hold that \( \bar{z}_t \geq d(x_t, X_f) \), thus case 3.b) occurs, and the values \( V_t = \bar{V}_t \) and \( z_t = \tilde{z}_t \) are set. Now, recalling that \( \tilde{z}_t = \max(0, z_{t-1} - d(x_{t-1}, X_f)) \), two cases may occur: either \( \tilde{z}_t = 0 \) or \( \tilde{z}_t = z_{t-1} - d(x_{t-1}, X_f) > 0 \). If \( \tilde{z}_t = 0 \), we have \( 0 = \tilde{z}_t \geq d(x_t, X_f) \), i.e. \( d(x_t, X_f) = 0 \), which would imply that the terminal set has been reached. Otherwise, if \( \tilde{z}_t = z_{t-1} - d(x_{t-1}, X_f) > 0 \), then we have:

\[
z_t = \tilde{z}_t \geq d(x_t, X_f) \geq 0, \tag{11}
\]

and \( z_t - z_{t-1} = \tilde{z}_t - z_{t-1} = z_{t-1} - d(x_{t-1}, X_f) - z_{t-1} = -d(x_{t-1}, X_f) \). Thus,

\[
z_t - z_{t-1} \leq -\varepsilon d(x_{t-1}, X_f), \quad \forall x_{t-1} \notin X_f, \tag{12}
\]

and \( z_t - z_{t-1} = 0 \iff x_{t-1} \in X_f \). \tag{13}\

On the other hand, if at step 3) of the MPC algorithm it happens that \( z_t^* \leq (z_{t-1} - \varepsilon d(x_{t-1}, X_f)) \), then case 3.c) occurs, and the optimal values \( V_t^* \) and \( z_t^* \) are retained, i.e. \( z_t = z_t^*, V_t = V_t^* \). In this case, it is straightforward to note that equations (11)-(13) still hold true. The same reasoning can be repeated for
any time step, as long as the case $z_t^* \leq (z_{t-1} - \varepsilon d(x_{t-1}, X_f))$ or $\tilde{z}_t \geq d(x_t, X_f)$ holds true as assumed, so that we can conclude that the variable $z_t$ enjoys the following properties:

$$
\begin{align*}
    z_t &\geq d(x_t, X_f) \geq 0, \forall t \geq 0; \\
    z_t = 0 &\iff x_t \in X_f; \\
    z_{t+1} - z_t &\leq -\varepsilon d(x_t, X_f), \forall x_t \notin X_f, \forall t \geq 0; \\
    z_{t+1} - z_t = 0 &\iff x_t \in X_f.
\end{align*}
$$

(14)

Properties (14) are sufficient to prove convergence of the state $x_t$ to the set $X_f$:

$$
0 \leq \lim_{t\to\infty} d(x_t, X_f) \leq \lim_{t\to\infty} z_t = 0, \Rightarrow \lim_{t\to\infty} d(x_t, X_f) = 0.
$$

Therefore, we obtain that in case $\hat{A}$ the MPC algorithm guarantees that $\lim_{t\to\infty} d(x_t, X_f) = 0$.

**II.** Let us next analyze what happens in case $A$. Let $\bar{t} > 0$ be the time instant at which the case $z_t^* > (z_{t-1} - \varepsilon d(x_{t-1}, X_f))$ and $\bar{z}_t < d(x_t, X_f)$ is met for the first time, and let $t^* < \bar{t}$ be the last time at which case $z_t^* \leq (z_{t-1} - \varepsilon d(x_{t-1}, X_f))$ was satisfied, that is the last time previous to $\bar{t}$ when an optimal command sequence was retained, together with its constraint violation $q_t^*$. According to case 3.c) of Algorithm 4.1; let $\ell = t - t^* \geq 1$. According to step 3.a) of the MPC algorithm, we set

$$
V_t = \hat{V}_t, \quad z_t = 0, \quad q_t = \bar{q}_t.
$$

(15)

Thus, at step 4) of the algorithm, the control move $u_t = K_t \hat{x}_t + v_{0|t}$ is applied to the system at time $t$, where $v_{0|t} = v_{0|t}^{\star}$, i.e., $v_{0|t}$ is the optimal correction predicted for time $t^* + \ell = \bar{t}$, computed at time $t^*$. At time step $t = \bar{t} - k$, the state variable $x_{\bar{t}+1}$ is observed and $(\hat{V}_{\bar{t}+1}, \tilde{z}_{\bar{t}+1}, \bar{q}_{\bar{t}+1})$ are computed as $\tilde{z}_{\bar{t}+1} = \max(0, z_t^* - d(x_{t-1}, X_f))$, $\bar{q}_{\bar{t}+1} = \bar{q}_t$, $\hat{V}_{\bar{t}+1} = \{v_j, N\} = \{v_{t+1}\}$, $v_{t+1}$, are computed at step 2), and we notice that, by definition, $z_{\bar{t}+1}^* \geq 0$. Therefore, at step 3) of the algorithm either (i) case 3.a) $(z_{\bar{t}+1}^* > (z_{t} - \varepsilon d(x_t, X_f))$ and $\tilde{z}_{\bar{t}+1} < d(x_{t}, X_f)$) is detected again, or (ii) one of cases 3.b) or 3.c) are detected, which would imply, respectively, $0 = \tilde{z}_{\bar{t}+1} \geq d(x_{t+1}, X_f)$, or $0 \leq d(x_{t}, X_f) \leq z_{\bar{t}+1}^* = \tilde{z}_{t+1} = 0$. Hence (in either case) $x_{t+1} \in X_f$, so that this convergence to the terminal set would be achieved. Consider then case (i): the values $V_{t+1} = \hat{V}_{t+1}$, $z_{t+1} = 0$ and $q_{t+1} = q_t$ are set in the algorithm, and the control move $u_{t+1} = K_{t+1}x_{t+1} + v_{t+1}^{\star}$ is applied to the system. Now, the same circumstances actually reproduce for all time steps $t = \bar{t} + k, k \geq 0$, so the algorithm is such that the optimal input sequence $\check{V}_t^*$, computed at time $t^*$ by solving a scenario FHOC, is the one actually next applied to the system, and the related constraint violation $q_t^*$ is retained for all $t \geq t^*$. Thus, in case $A$, there exists a finite time $t^*$ such that the sequence $V_t^*$ is applied to the system for all subsequent instants $t = t^* + k, k = 0, \ldots, N - 1$. Now, the sequence $V_t^*$ is the result of the solution of the scenario-FHOC $P(x_t, \omega_t)$, and Proposition 3.3 states that, with practical certainty, we have $R(\omega_t) \geq \rho$, where $R$ is the reliability defined in Section III-A of the paper, which means that $P \{ \delta : h(s_t, x_t, \delta) \leq 0 \} \geq \rho$. Therefore, in the situation $A$, there exists a finite time $t^*$ at which an optimal control sequence is computed by solving a scenario-FHOC and next applied to the actual system for the subsequent $N$ time instants: we can hence claim with practical certainty this sequence will satisfy the problem constraints and reach the terminal set within the time window from $t^*$ to $t^* + N$, with probability at least $p$ and constraint violation $q_t^*$.

5 Numerical example

We consider the system (11) with: $A(\theta) = \begin{bmatrix} 1 + \theta_1 & 1 \\ 0.1 \sin(\theta_1) & 1 + \theta_2 \end{bmatrix}$, $B(\theta) = \begin{bmatrix} 0.3 \arctan(\theta_3) \\ 1 \end{bmatrix}$, $B_3 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$. Each of the random parameters $\theta_1, \theta_2, \theta_3$ is uniformly distributed in the interval $[-0.1, 0.1]$, while $\theta_4, \theta_5$ are distributed according to Gaussian distributions with zero mean and unit variance. Moreover, the disturbance $\gamma_t \in \mathbb{R}^2$ is computed as follows:

$$
\gamma_t = \begin{cases}
    \eta_1, \min \left( \eta_2, \frac{1}{\rho(\eta_3, \eta_4, \eta_5)} \right) & \text{if } \eta_0 \geq 0.5 \\
    0.05 \cos(\eta_1), \eta_5 & \text{if } \eta_0 < 0.5
\end{cases}
$$

if $\eta_0 \geq 0.5$ and $\eta_5 < 0.5$. The disturbance is applied to the system for all subsequent instants.
where
\[ \eta_3 = \max \left( \min \left( \eta_4 \sin \left( \frac{x}{4} \right), 0.05 | \sin (\eta_3) | \right), -0.05 | \sin (\eta_3) | \right) \]
and \( \eta_0 \in [0, 1], \eta_1 \in [0, 0.05], \eta_2 \in [0, 0.05], \eta_3 \in [\frac{\pi}{4}, \frac{\pi}{4}], \eta_4 \in [-0.05, 0.05] \) are uniformly distributed random variables. We also consider the following constraints on the input and state variables: \( X(\theta) = \{ x \in \mathbb{R}^2 : \| x \| \leq \pi(\theta) \}, \ U(\theta) = \{ u \in \mathbb{R} : | u | \leq \pi(\theta) \}, \pi(\theta) = 5/(1+\theta_6 \sin(\theta_7)), 10/(1+\theta_6 \cos(\theta_7)) \}'s, \( \theta_6 \in [-0.05, 0.05] \) is uniformly distributed, finally \( \theta_7 \) is distributed according to a Gaussian distribution with zero mean and unit variance. Note that the system matrices and constraints are a nonlinear functions of the uncertain parameters, and the disturbance belongs to a non-convex, disconnected set. Hence, no existing technique for robust MPC can be directly applied in this example. By using the results in [21][22] (see Section 3, we computed the terminal control law \( K_f \) and terminal set \( X_f \) satisfying Assumption 3. \( K_f = [-0.4686, -1.4221], \ X_f = \{ x \in \mathbb{R}^2 : x^T Q_f x \leq 1 \} \). We designed the MPC law with \( N = 10 \) and \( \Lambda = 1 \). We set \( \beta = 10^{-9} \), and considered different values of \( p \). In order to estimate the probability with which the MPC control law \( V^*_f \) satisfy the constraints and drive the state to the terminal set, and to compare it with the bound \( p \), we carried out \( N_{\text{trials}} = 100,000 \) Monte Carlo simulations, starting from the same initial state \( x_0 = [5, 2.75]^T \). We note that this initial condition is not feasible for the deterministic counterpart of the scenario problem, hence for some extractions of \( \omega_0 \) to the constraint violation \( q^*_0 \) is not negligible. In each one of these simulations, Algorithm 4.1 has been applied and the probability of success \( \hat{p} \) has been estimated as \( \hat{p} = \frac{N_{\text{trials}} - N_{\text{failures}}}{N_{\text{trials}}} \), where \( N_{\text{failures}} \) is the number of simulations in which some of the constraints were not satisfied. Moreover, the finite horizon solution was also tested, to check the result of Proposition 5.1. In particular, for the finite horizon sequence \( V^*_f \), the considered constraints were the state and input constraints \( X(\theta), U(\theta) \), and the terminal set constraint \( x_N \in X_f \), while for the receding horizon implementation the latter constraint was replaced with \( x_{N+10} \in X_f \), in order to approximately take into account the asymptotic stability result of Theorem 4.1 (b)-(i). We evaluated these constraints as hard constraints, i.e. with zero constraint violation. The values of \( \hat{p} \) for the finite horizon simulations and for the receding horizon ones are indicated as \( \hat{p}^{\text{FH}} \) and \( \hat{p}^{\text{RH}} \), respectively.

| \( M(p) \) | \( \hat{p}^{\text{FH}} \) | \( \hat{p}^{\text{RH}} \) |
|---|---|---|
| 22 (0.05) | 0.885 | 0.921 |
| 42 (0.30) | 0.901 | 0.943 |
| 95 (0.60) | 0.923 | 0.963 |
| 890 (0.95) | 0.993 | 0.999 |

The obtained results are reported in Table 1 for values of \( p = 0.05, 0.3, 0.6, 0.95 \). The corresponding values of \( M \) are also reported in the Table. It can be noted that in all cases the values of \( \hat{p}^{\text{FH}}, \hat{p}^{\text{RH}} \) are higher than the corresponding \( p \), in accordance with the theoretical results of Sections 4.1. Moreover, the values of \( \hat{p}^{\text{FH}} \) are lower than those of \( \hat{p}^{\text{RH}} \). The estimated probabilities of success \( \hat{p}^{\text{FH}}, \hat{p}^{\text{RH}} \) are quite good already with low values of \( M \): in the finite horizon case, the reason of such a good result is mainly the presence of the terminal control law \( K_f \), which has already some degree of robustness, while in the receding horizon case, a higher robustness derives from the iterative re-optimization of the corrective control sequence \( V^*_t \). It is worth to notice that the value of \( M \) does not depend on the dimension of the state variable or of the uncertainty/disturbance variables; it only depends on the chosen values of \( p, \beta \) and on the number of decision variables in the scenario FHOCP, i.e., the number \( m \) of inputs multiplied by the control horizon \( N \), plus the slack variables \( z \) and \( q \). However, the number of constraints embedded in \( h(s, x, \delta) \) depends linearly on \( n, m \) and \( N \), so that the growth of the overall number of constraints in the scenario problem, for fixed values of \( p \) and \( \beta \), is \( \sim (n \cdot m^2 \cdot N^2) \), i.e., quadratic with respect to the control horizon.  

Table 1: Numerical example. Estimates \( \hat{p} \) of the probability of success for different values of \( p \), with \( \beta = 10^{-9} \).
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