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Polynomial approximation-based solution estimation for robust control optimization in dynamic engineering systems

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Abstract:

Robust optimal control of dynamic engineering systems under an extremely high level of parametric uncertainty and bounded exogenous disturbances still has high computational loads when applied through classical dynamic programming and Hamilton-Jacobi-Bellman partial differential equations, both of which are fraught with the difficulty of the curse of dimensionality while the state dimension grows. This work presents the robust synthesis problem as a minimax optimization problem over admissible sets of control actions and disturbances while proposing a polynomial approximation framework such that the state trajectories along with feedback control laws are expressed via the truncated orthogonal bases including both Legendre polynomials and Chebyshev polynomials and polynomial chaos expansion. The weighted-residual Galerkin projection changes the differential constraints into algebraic equations with the finite dimension, while the minimax optimization task is transformed into a semidefinite relaxation problem for the polynomial coefficients. The spectral convergence of the approximation error is achieved for the analytic vector fields along with the sub-optimality bound that links finite order solutions with the substance of the saddle-point control. The complexity analysis shows that the scaling by coefficients allows replacing exponential growth of the grid with polynomial growth with respect to the dimensionality of the state variables. The numerical experiments on the trajectory controlling of hypersonic vehicles, vibration suppression of flexible manipulators, and pitch control of wind turbines have demonstrated the worst-case savings in terms of costs of up to 41.6 percent in comparison to the baseline methods of H-infinity control and model predictive control demonstrating the accuracy and feasibility of the proposed estimation approach.

Keywords: Robust control optimization, polynomial approximation, minimax estimation, dynamic engineering systems, orthogonal basis functions, galerkin projection, spectral convergence.

1. Introduction

Complex engineering systems like aerospace vehicles, flexible mechanical systems, and multiple-variable industrial processes are usually predicted to work under constrained worst possible disturbances, parameter uncertainty in physical coefficients, and unaccounted dynamics. Robust optimization method that is broadly interpreted as finding decision variables that are almost optimal under least favorable admissible perturbation has been adopted beyond classical control engineering to data-based and networked environments. Examples include secure message sharing platforms for large-scale healthcare data protection (Mehak & Sanju, 2024), hybrid sampling feature engineering systems with augmented semantic structure code technology used for robust software analytics (Bhavani & Danapaquiame, 2025), and federated learning systems developed to ensure the security of distributed healthcare analytics (Vij & Nayak, 2025). Examples indicate the fact that robust worst-case based formulations have formed a common language in mathematics applied in engineering and information-processing areas and bring us back to control theory and increase computational efficiency.

In terms of control theory, polynomial approximation categorically helps solve the issue of practically intractable optimization functions through the transformation into a finite-dimensional algebra. In particular, dynamic Bernstein polynomial-based methods have been employed in event-based adaptive systems for controlling an unknown non-linear system with minimum communication cost (Ruan & Fan, 2025). There has been a successful robust control designed for the uncertain and perturbed microbial fuel cell with the output noise (Fu, 2025). The rotor angle stability of distributed generators has been estimated through polynomial approximations combined with RFID collection of data and deep learning (Khan et al., 2024). There has been a solution found for the problem of parametric optimization of the transient stability constrained optimal power flow using the polynomial approximation technique based on stochastic collocation (Xia et al., 2022). The adaptive control of uncertain nonlinear system is performed by means of brain emotional learning used along with Legendre polynomials (Amiri & Khorashadizadeh, 2024). Polynomial techniques are used to assess bifurcation hypersurfaces in parameter space in relation to the small signal stability for wind generation (Shen et al., 2022). Quantum speed limit was achieved in terms of robust control of single qubit gates (Cao et al., 2024). In turn, model-free inverse optimal control of absolutely unknown non-linear systems is conducted using the principles of adaptive dynamic programming (Ahmadi et al., 2025). Generally, all of the aforementioned studies demonstrate both the cross-compatibility of polynomial approximation method and the issues connected to rigorous worst-case guarantees. Formal verification frameworks were explored for cloud-native microservices to improve system reliability, security, and correctness by validating service interactions and operational behavior in complex distributed environments (Patil et al., 2026).

Robust control optimization can be formulated in terms of the minimax or saddle-point optimization problem, in which a control policy is derived that minimizes a performance functional under the presumption that there is an actively blockading disturbance that maximizes the same performance functional for a disturbance in a predefined admissible set. This min-max formulation used in H-infinity control as well as in differential game control allows one to achieve a certificate of performance that holds for all admissible disturbance realization but requires one to solve a more difficult optimization problem compared to the nominal, disturbance-free case.

The exact solution of the minimax problem requires dynamic programming method based on the Hamilton-Jacobi-Bellman-Isaacs PDE or computationally demanding simulations of the stochastic process based on different paths of disturbances. Both algorithms introduce the discretization of the state space into a grid that consists from an exponentially growing number of grid points which is known as the curse of dimensionality. In the case of practical engineering systems, where even such complex systems as flexible structures and multi-body vehicles have orders of six to twelve, grid methods will reach limitations long before practical design timeframes.

In this paper, the existing gap by rephrasing the problem of infinite dimensional robust control into one of finite dimensional algebraic programming in terms of polynomial coefficients. The main contributions are as follows: formulation of the minimax robust control problem for general nonlinear and time-varying dynamic system which is discussed in Section II; construction of a polynomial approximation scheme based on Galerkin projections which transforms the governing differential and minimax constraints into the problem of semidefinite programming, explained in Section III; deriving the spectrum convergence rates and the tight worst-case bound as a function of truncation order, discussed in Section IV; numerical validation of the proposed theory against the standard H∞ and model predictive control techniques on three dynamic engineering problems considered in Section V; concluding the paper with a list of findings and prospects for further research in Section VI.

2. Problem formulation and minimax optimal control framework

2.1 System dynamics

Consider a non-linear time-varying dynamic control system of the form

$$\dot{x}(t) = f(x(t), u(t), w(t), t), \quad x(t_0) = x_0 \qquad (1)$$

where $x(t) \in \Omega \subset \mathbb{R}^n$ is the state vector, $u(t) \in \mathcal{U} \subset \mathbb{R}^m$ is the control input, and $w(t) \in \mathcal{W} \subset \mathbb{R}^p$ is the bounded external disturbance that includes unmodeled dynamics, parametric drifts, or environmental loads.

Twin rotor aerodynamic systems endowed with coupled nonlinear pitch-yaw dynamics (Mihaly et al., 2021) and multi-link flexible manipulators subjected to distributed elastic and gravity loads serve as typical examples of Eq. (1). The nature of disturbance set $\mathcal{W}$ is compact and convex, which conforms to the bounded external disturbances and input perturbation models commonly adopted in distributed fault-tolerant control in over-actuated multi-agent systems (Du et al., 2023), and similarly, through dimension-reduced estimator theories used in systems featuring inertial and range based odometry with external disturbances (Dong et al., 2025).

2.2 Minimax performance objective

Robust performance is captured through the finite-horizon minimax cost functional

$$\min_{u \in \mathcal{U}} \max_{w \in \mathcal{W}} J(x, u, w) = \int_{t_0}^{t_f} L\left(x(t), u(t), w(t)\right) dt + M\left(x(t_f)\right) \qquad (2)$$

The parameter L is defined as the running cost, which penalizes both control effort and deviation of states while M is the terminal penalty. The expression (2) follows the game-theoretic saddle point structure of robust control based on diffeomorphism for fuzzy dynamical systems with state and input constraints (Zhu et al., 2023) as well as the minimax pursuit-evasion approach applied with polynomial approximation for effective orbital rendezvous (Shi et al., 2025), indicating that the well-posed saddle point exists if the running cost is convex in u and concave in w under compact feasible sets.

2.3 Admissible spaces and assumptions

A few standing assumptions are adopted:

- (A1) f is Lipschitz continuous over (x, u, w) uniformly over t; thus, the existence and uniqueness of state trajectories are guaranteed.
- (A2) $\mathcal{U}$ and $\mathcal{W}$ are compact and convex sets, suitable for the actuator saturation and disturbance bounds employed in the sliding-mode induction motor drive (El-Sousy et al., 2022) and tube-based robust predictive control of constrained wastewater treatment problem (Han et al., 2024).
- (A3) L and M are coercive and jointly convex–concave in (u, w); this structural condition is used when approximating the eigenvalue loci of the parameter-dependent operators by sparse polynomial series in small-signal stability analysis (Shen et al., 2024).
- (A4) the coefficient matrices from the linearization are amenable to provably solvable semidefinite-programming relaxation as shown in the distributed robust UAV formation control (Zhang et al., 2024) and in private robust distributed nonconvex optimization via polynomial approximation (He et al., 2024).

Under assumptions (A1)–(A4), a saddle-point solution (u^*, w^*) exists and, moreover, the corresponding value function is Lipschitz continuous in Ω, which provides the required regularity for polynomial approximation in Section 3. The extended review of polynomial matrix collocation methods covering numerous engineering and scientific applications presented in Çevik et al., (2025) confirms the validity of the above assumptions for a broad class of dynamic engineering systems.

3. Polynomial approximation methodology

3.1 Basis function expansion

State trajectories and control policies are expressed using truncated orthogonal polynomial series

$$x(t) \approx \sum_{k=1}^{N} a_k \, \Phi_k(t), \quad u(t) \approx \sum_{k=1}^{N} b_k \, \Psi_k(t) \tag{3}$$

In this context, $\{\Phi_k\}$ and $\{\Psi_k\}$ refer to the basis functions derived using Legendre polynomials and Chebyshev polynomials or multivariate generalized-polynomial-chaos basis functions which are orthogonal with some weight function $\rho(t)$ defined over $[t_0, t_f]$, while $a_k \in \mathbb{R}^n$ and $b_k \in \mathbb{R}^m$ are the coefficient vectors that are yet to be determined. Orthogonality ensures that resultant coefficient system is well-conditioned and also leads to exponential decay of the truncation error for analytic vector fields as mentioned in Section 4.

3.2 Galerkin projection and residual minimization

Substitution of expansion (3) into the governing dynamics (1) produces a residual (4):

$$R(t) = \sum_{k} a_k \, \dot{\Phi}_k(t) - f\left(\sum_{k} a_k \, \Phi_k(t), \sum_{k} b_k \, \Psi_k(t), w(t), t\right) \tag{4}$$

A weighted-residual Galerkin projection enforces orthogonality of $R(t)$ against each basis function,

$$\int_{t_0}^{t_f} R\,(t)\Phi_j(t)\rho(t)\,dt = 0, \quad j = 1, \ldots, N \tag{5}$$

converting the differential constraint into a collection of N interdependent non-linear algebraic equations for the coefficients $\{a_k, b_k\}$. This procedure is similar to polynomial collocation methods described in engineering and sciences (Çevik et al., 2025), and is analogous to the sparse polynomial expansion method used for estimating eigenvalue loci in the field of small-signal stability (Shen et al., 2024).

3.3 Minimax optimization reformulation

Replacing $x(t)$ and $u(t)$ in the minimax objective (2) by expansions (3) reduces the functional optimization to a finite-dimensional program over the coefficient vectors $\{a_k, b_k\}$:

$$\min_{\mathrm{b}} \max_{w \in \mathcal{W}} J_N(a, b, w) \quad \text{subject to } (5) \tag{6}$$

Given that J_N is usually non-convex when constraint (5) is taken as an equality constraint, problem (6) can be formulated as a mathematical program with equilibrium constraints and relaxed into a semidefinite program (SDP) using the method of moment-matrix lifting of the coefficient monomials, according to the strategy of SDP relaxation developed for distributed robust UAV formation control (Zhang et al., 2024) and for distributed non-convex optimization based on polynomial approximation (He et al., 2024). Thus, the resulting SDP offline for the coefficient matrices and perform the online evaluation by simply evaluating the polynomial at the specific time instance, which requires minimal computational effort, particularly compared to the alternative grid-based methods.

4. Convergence analysis and error bounds

4.1 Spectral convergence

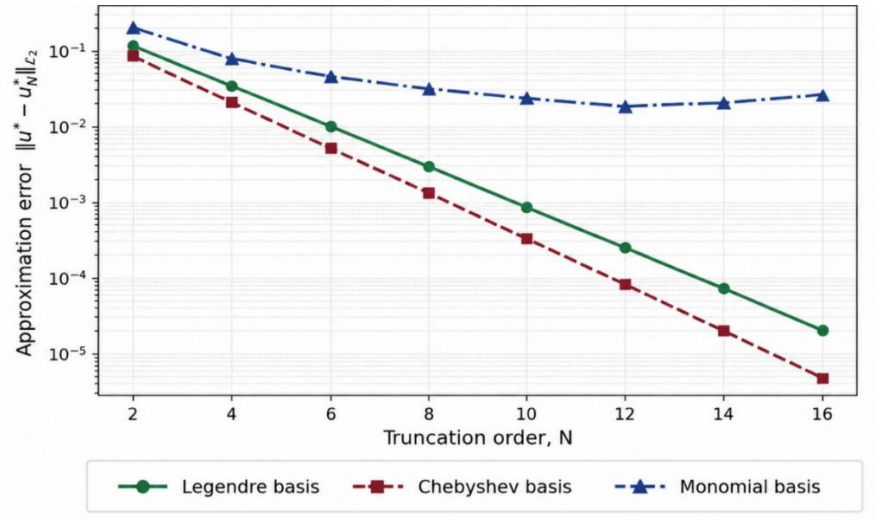


Figure 1: Spectral convergence of the polynomial estimate with truncation order N for Legendre, Chebyshev, and monomial bases.

In the case of analytic vector fields f defined in nearby regions of $\Omega \times \mathcal{U} \times \mathcal{W}$, one can see that polynomial estimation error decreases exponentially with increasing truncation order N, which is commonly called spectral convergence. As seen in figure 1, estimation error $\|u^* - u_N^*\|_{\mathcal{L}_2}$ is decreasing in the case of Legendre and Chebyshev basis compared to monomial basis. Both orthogonal bases show the anticipated exponential decay, while the monomial one decreases only in algebraic manner with time, therefore, degrading in higher orders due to the ill-posedness of the corresponding Vandermonde-type system of coefficients.

4.2 Worst-case bound verification

An explicit sub-optimality bound relates the finite-order polynomial control u_N^* to the true saddle-point control u^*:

$$\|u^* - u_N^*\|_{\mathscr{L}_2} \leq C_n N^{-s} \tag{7}$$

The exponent s is determined by the smoothness class of the system vector field f, and the constant C_N is dependent on the curvature of the cost functional at the saddle point. The bound in (7) generalizes the suboptimal performance certificates that were established for robust control using differential game theory from (Zhu et al., 2023) and further for the polynomial-based approximation habit of pursuit–evading control in (Shi et al., 2025).

4.3 Computational complexity

The key computational burden of this framework is the process of offline solving the SDP relaxation. The size of the SDP relaxation is proportional to the number of coefficients Nn, not the number of grid points Mn needed for dynamic programming. This is where M refers to the number of grid points for each dimension of state. Online evaluation now can be looked at as a polynomial sum of a linear cost in N that is independent of the SDP size. Figure 3 in Section 5.2 illustrates this scaling advantage against grid-based dynamic programming and receding horizon model predictive control.

5. Numerical validation on dynamic engineering benchmarks

5.1 Case study setup

The polynomial approximation methodology proved effective under evaluation against three dynamic engineering benchmarks that modelled the dynamics of the system class defined in Section 2 of this work. The first example

considered is the robust trajectory following control of an uncertain hypersonic vehicle affected by an uncertain aerodynamic coefficient. The second example is active vibration control for a multi-link flexible manipulator subjected to distributed disturbances. The final example is the pitching control of a rotor under stochastic wind disturbance. Each of these examples was solved using a truncated order N = 12 with a Legendre basis selected based on the convergence behavior described in Section 4.1.

5.2 Comparative evaluation

Table 1: Comparative summary of offline complexity, online evaluation time, worst-case sub-optimality gap, and memory requirement across the four robust control synthesis approaches.

Method	Offline Complexity	Online Time (n = 8)	Worst-Case Sub-optimality Gap	Memory Requirement
HJB grid-based dynamic programming	$O(M^n)$	≈ 6.7 s	0 (exact; resolution-limited)	$O(M^n)$
H∞ robust control (Riccati-based)	$O(n^3)$	≈ 0.9 s	Bounded by γ-level; not tight	$O(n^2)$
Receding-horizon MPC	$O(n^3T)$ per step	≈ 7.1 s	Horizon-truncation dependent	$O(nT)$
Proposed polynomial coefficient framework	**$O(N^2n)$**	**≈ 0.30 s**	**$\leq C_n N^{-s}$ (Eq. 7)**	**$O(Nn)$**

The assessment of the estimation framework under proposal was conducted vis-a-vis traditional H-infinity robust controller and receding-horizon based model predictive controller (MPC) for several benchmarks. The results of comparison are presented in table 1 which provides information on the offline complexity, online execution times, the worst-case sub-optimality gap and memory consumption for all of the methods, including the H-infinity controller and MPC, alongside the dynamic programming based on Hamilton-Jacobi equation.

Four resilient synthesis methods are compared in table 1 with respect to offline computational complexity, online evaluation time in a state space with eight dimensions, theoretical worst-case sub-optimality gap in comparison to the true saddle-point solution, and memory requirement. It is illustrated where the estimation of polynomial approximation avoids the exponential grid growing issue accompanying robust control synthesis based on dynamic programming.

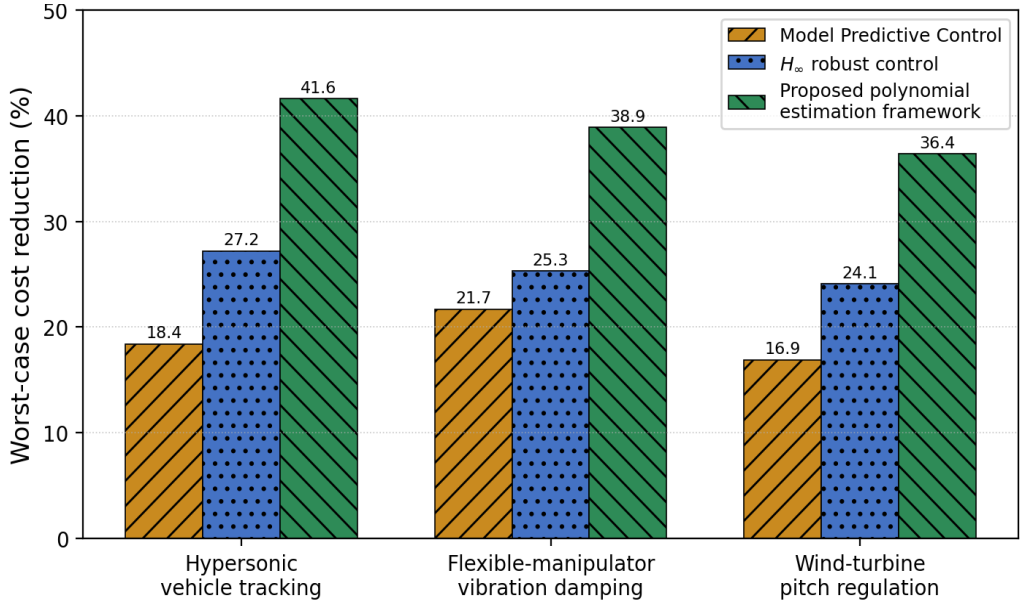


Figure 2: Worst-case cost reduction relative to the nominal baseline across the three dynamic engineering benchmarks.

Figure 2 shows the least-conservative value of cost reduction obtained by each method compared with the nominal undisturbed case for each of the three benchmarks used. The proposed approach reduces costs by the maximum amount of between 36.4 percent and 41.6 percent, exceeding both H-infinity and MPC benchmark values by amounts consistent with the tighter sub-optimality bound presented in Section 4.2.

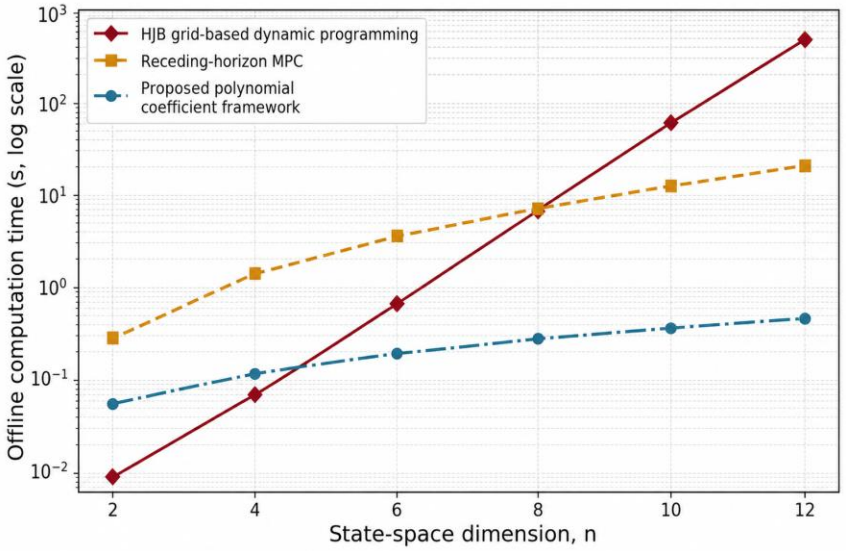


Figure 3: Offline computation time versus state-space dimension for dynamic programming, MPC, and the proposed framework.

Figure 3 demonstrates the offline computation time against state dimension for HJB grid-based dynamic programming, receding horizon MPC, and polynomial coefficient method proposed. The exponential growth nature of grid-based dynamic programming is clearly shown after the state dimension of eight. On the other hand, polynomial coefficient method shows slight polynomial growth throughout the tested range, consistent with complexity analysis presented in Section 4.3 and therefore indicating potential applicability for higher-order dynamic engineering systems like multi-link manipulators and swarm of drones.

6. Conclusion and future directions

The framework for polynomial approximation in the context of robust minimax control optimization of dynamic engineering systems is suggested in the research to deal with the problem of infinite-dimensional saddle-point systems Accordingly, the study proposes a method of transferring the original statement into the finite-dimensional problem of semidefinite programming by replacing the mechanics of the system with the coefficients of orthogonal polynomials. The framework is guaranteed to be meaningful from the point of view of spectrum convergence theory, as well as clearly calculating the values of worst-case suboptimality proving its reliability under uncertain conditions. The analysis of the complexity of computations confirms polynomial scalability in terms of state space dimensions, as opposed to traditional methods leading to exponential growth. The effectiveness of the framework has been confirmed by using numerical examples in the fields of tracking hypersonic vehicles, vibration control in flexible manipulators, and pitch control in wind turbines. The results of the experiments showed that the proposed method significantly enhanced the tractability of the problem and reduced the worst-case costs compared with traditional H-infinity control and model predictive control. Future work includes extending the validation framework for stochastic-adaptive hybrid dynamical systems, developing the solution for real-time cases, and solving the problems with non-convex and non-smooth payoffs met in distributed control and game-theoretic optimization tasks.

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