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MULTI-CRITERIA CONTROL OF LARGE-SCALE NONLINEAR DYNAMICAL SYSTEMS WITHOUT LINEARIZATION, BASED ON LYAPUNOV FUNCTIONS

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Abstract. This paper proposes a numerical control method for large-scale nonlinear dynamical systems, focused on maintaining stability without using linearization. The approach under study is based on the principles of multi-criteria optimization, where the stability of the system is directly included in the vector of target criteria through Lyapunov functions. This allows us not only to minimize deviations from the target states and energy consumption for control, but also to guarantee the asymptotic stability of the system under arbitrary initial conditions. A mathematical formulation of the problem is presented, a discrete numerical control scheme is developed, and a scalarization strategy is proposed that provides an approximation to Pareto-optimal solutions. A series of numerical experiments implemented in Python has been conducted, confirming the effectiveness of the method using examples of both single- and multi-agent systems. The results demonstrate the stable behavior of the trajectories, a decrease in the Lyapunov function over time and correct operation even with strong nonlinearity of the model.

Keywords: nonlinear systems, stability, Lyapunov function, multi-criteria optimization, distributed control, numerical simulation, control without linearization

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МНОГОКРИТЕРИАЛЬНОЕ УПРАВЛЕНИЕ КРУПНОМАСШТАБНЫМИ НЕЛИНЕЙНЫМИ ДИНАМИЧЕСКИМИ СИСТЕМАМИ БЕЗ ЛИНЕАРИЗАЦИИ НА ОСНОВЕ ФУНКЦИЙ ЛЯПУНОВА

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Аннотация. В данной статье предлагается метод численного управления крупномасштабными нелинейными динамическими системами, ориентированный на сохранение устойчивости без использования линеаризации. Исследуемый подход опирается на принципы многокритериальной оптимизации, где устойчивость системы напрямую включается в вектор целевых критериев посредством функций Ляпунова. Это позволяет не только минимизировать отклонения от целевых состояний и энергозатраты на управление, но и гарантировать асимптотическую устойчивость системы при произвольных начальных условиях. Представлена математическая постановка задачи, разработана дискретная численная схема управления и предложена стратегия скаляризации, обеспечивающая приближение к Парето-оптимальным решениям. Проведена серия численных экспериментов при помощи языка программирования Python, результаты моделирования представлены в виде графиков, подтверждающих эффективность метода на примере как одиночной, так и мультиагентной системы. Результаты демонстрируют устойчивое поведение траекторий, уменьшение функции Ляпунова во времени и корректную работу даже при сильной нелинейности модели.

Ключевые слова: нелинейные системы, устойчивость, функция Ляпунова, многокритериальная оптимизация, распределенное управление, численное моделирование, управление без линеаризации

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Introduction

Modern technical, cyber-physical and social systems are characterized by high dimensionality, a complex structure of interactions between components and pronounced nonlinear dynamics [1]. Such systems include intelligent power grids, multi-agent robotic platforms, traffic management systems, distributed computing complexes and others [2, 3]. Increasing complexity creates the need for new control approaches, the necessity to simultaneously consider multiple quality criteria, interactions between subsystems, and stability requirements [4, 5].

Traditional control methods based on linearization of the model demonstrate limited applicability under conditions of rapid transients, saturation of control actions and variable system structure. In particular, linearization can significantly distort the real properties of the system, reducing control accuracy and depriving the developer of stability guarantees outside a small neighborhood of the equilibrium [6].

In these conditions, multi-criteria optimization (MCO) without linearization becomes particularly relevant, allowing for simultaneous consideration of dynamic and energy characteristics, as well as stability characteristics [7–10]. However, most existing approaches to MCO treat stability as an additional constraint or a posteriori verification of results, without including it in the optimization structure itself. This creates a gap between the formal optimization task and the actual requirements for the safety and stability of the system [11—14].

The present work introduces an approach in which the Lyapunov function is included directly in the vector of criteria for MCO. This allows for integrating stability requirements into the optimization process. This approach can be applied in both centralized and distributed control systems.

Mathematical model and formalization of multi-criteria control

Structure and properties of the controlled system

By a large-scale nonlinear system, we mean a set of M interacting subsystems $\sum i$, each of which has its own dynamics and interacts with others through a limited set of connections. The connectivity of the system is represented by an oriented graph $G = (V, E)$, where the vertices $V = \{1, 2, ..., M\}$ correspond to subsystems, and the edges $E \subset V \times V$ determine the structure of the interaction [15, 16].

The dynamics of each subsystem $\sum i$ is given by a system of differential equations:

$$\dot{x}_i = f_i\left(x_i,\, u_i,\, x_{N_i}\right), \quad y_i = h_i\left(x_i\right),$$

where: $x_i \in \mathbb{R}_i^n$ is the state vector; $u_i \in \mathbb{R}_i^m$ is the control input; $N_i \subset V$ is a set of neighboring agents with which there is a connection that affects subsystems $\sum i$; x_{N_i} is the vector of all neighboring states; f_i, h_i is the continuous functions, and in some cases, non-linear ones.

The state of the entire system:

$$x = \left[x_1^T,\, x_2^T,\, \dots,\, x_M^T\right]^T \in \mathbb{R}^n, \quad n = \sum_{i=1}^{M} n_i.$$

Problem formulation for multi-criteria control

Modern control tasks require simultaneous satisfaction of several, often contradictory, goals: minimizing deviations from the trajectory, reducing control effort and ensuring stability and coordination between system components [17—20]. Formally, such a task is formulated as a MCO with a vector objective function:

$$J\left(x,\, u\right) = \begin{bmatrix} J_1\left(x,\, u\right) \\ J_2\left(x,\, u\right) \\ \vdots \\ J_K\left(x,\, u\right) \end{bmatrix}, \quad J_K : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}.$$

The desired control $u(t)$ must be Pareto-optimal for the vector of criteria $J(x(t)),\, u(t))$ under the following constraints:

1. Equations of motion of each subsystem:

$$\dot{x}_i = f_i\left(x_i,\, u_i,\, x_{N_i}\right).$$

2. Initial conditions:

$$x_i\left(0\right) = x_{i0}.$$

3. Functional constraints on control and state:

$$u_i(t) \in U_i,\quad x_i(t) \in X_i,\quad \forall t \in [0, T].$$

Stability as an integrated criterion: the Lyapunov function

The key feature of the proposed approach is the direct inclusion of the stability requirement in the objective function of the optimization problem. This is achieved through a Lyapunov function $V(x)$ that satisfies the classical conditions:

$$V(x) > 0 \text{ at } x \neq 0,\quad V(0) = 0;$$
$$\dot{V}(x) = \nabla V(x)^T f(x, u) < 0.$$

Using the Lyapunov function as one of the optimization criteria allows one not only to ensure the stability of the system, but also to integrate the quality of the transition process into the objective vector. The structure of the objective functions may include:

- control accuracy:

$$J_1 = \int_0^T \left\| x(t) - x_{ref}(t) \right\|^2 dt,$$

where $x_{ref}(t)$ is the desired trajectory;

- control effort:

$$J_2 = \int_0^T \left\| u(t) \right\|^2 dt.$$

- stability:

$$J_3 = V(x(T)).$$

- convergence rate:

$$J_4 = \int_0^T -V(x(t))\, dt.$$

For systems with polynomial nonlinearity, it is possible to use sums of squares of polynomials, which makes it possible to efficiently construct and verify Lyapunov functions via semidefinite programming:

$$V(x) \in \Sigma_{[x]},\quad -\dot{V}(x) = -\nabla V(x)^T f(x) \in \Sigma_{[x]}.$$

Distributed problem formulation

When implementing control in a distributed environment, each agent solves a local optimization problem, taking into account its objectives and coordination with its neighbors. In this case, the optimization takes the following form:

$$J_i = \sum_{k=0}^{N-1} \left[V_i\left(x_i^k\right) + \rho \left\| x_i^k - \overline{x}_{N_i}^k \right\|^2 + \beta \left\| u_i^k \right\|^2 \right],$$

where: $\overline{x}_{N_i}^k$ is the weighted average of the states of the neighbors; ρ, β are the coefficients of coordination and control effort.

Information exchange between agents takes place according to a certain topology of the graph $G = (V, E)$, and coordination can be implemented either via consensus iterations or via the Alternating Direction Method of Multipliers (ADMM).

Development of a numerical method for multi-criteria optimization

Requirements for the numerical algorithm

The following key requirements apply for the practical implementation of the proposed optimization method:

1) working with the original nonlinear model – without prior linearization;
2) multi-criteria capability – the presence of several goals in the objective function, including stability;
3) numerical stability – maintaining the operability of the method under coarse approximations;
4) distributed implementation – the ability to perform optimization independently for each subsystem with coordination;
5) flexibility – the ability to adapt to the constraints and changing structure of the model.

These requirements impose restrictions on the choice of integration method, convergence criteria and the structure of the computational process.

Discretization of dynamics

For numerical analysis, the continuous dynamics of the system is discretized in time. The simplest Euler scheme is used:

$$x_{k+1} = x_k + \Delta t \times f\left(x_k,\ u_k\right),\quad k = 0,\ \ldots,\ N-1,$$

where: Δt is the time step; N is the number of discretization steps.

With this scheme, the state sequence x_k is generated sequentially using the control values u_k.

In the future, the Euler scheme can be replaced by more stable schemes – Runge–Kutta or the backward Euler scheme.

The system is constrained by physical bounds, the states and controls are clipped to prescribed ranges:

$$x_k \in X = \left[-X_{\max},\ X_{\max}\right],\quad u_k \in U = \left[-u_{\max},\ u_{\max}\right].$$

Structure of the scalar functional

For numerical solution, the multi-criteria problem is scalarized – one combined functional is formed [21, 22]:

$$J\left(u\right) = \alpha \sum_{k=0}^{N-1} V\left(x_k\right) \times \Delta t + \beta \sum_{k=0}^{N-1} u_k^2 \times \Delta t,$$

where: $V(x_k)$ is the the Lyapunov function at step k; u_k is the control input.

The parameters α, β are set by the user and reflect the priority between stability and control effort.

This approach has the following advantages:

1. **Stability is included in the objective function**, which guarantees a decrease in $V(x)$ along the optimal trajectory. It is important to note here that stability is treated not as a hard **constraint**, but as one of the criteria.
2. After discretization and scalarization, the usual function $J(u)$ is obtained and **the problem can be solved numerically using Python** and scipy.optimize.minimize or other standard nonlinear optimizers.
3. **The algorithm is simple to implement in real time**. If N is chosen to be small, control can be computed in a few seconds, without complex squares of polynomials or semidefinite programming solvers, in the proposed algorithm the control action is updated at each control cycle.

Integration of Lyapunov conditions

To integrate stability into a numerical algorithm, it is necessary:

- fix the parameter $\delta > 0$;
- introduce a restriction:

$$\dot{V}(x_k) = \nabla V(x_k)^T f(x_k, u_k) \le -\delta \|x_k\|^2 .$$

If $V(x)$ is a quadratic or polynomial function (for example, $V(x) = x^T Px$), then verification of this condition is possible numerically. At the same time, the feasibility of the optimization problem remains, even if the exact minimum is not achieved, due to the preservation of the stability property.

Optimization algorithm

The general numerical scheme is as follows:

1. Initialization:
- the initial state x_0 is set;
- the parameters N, Δt, α, β are set;
- an approximation of $f_d(x, u)$ is chosen (for example, using the Euler method);
- an initial control guess $u^{(0)}$ is selected (for example, zeros).
2. Optimization:
- the objective functional $J(u)$ is constructed;
- the optimization method is chosen (gradient, quasi-Newton, evolutionary);
- if necessary, restrictions and filtering of values are introduced.
3. Stability check:
- it is necessary to make sure that the values of $V'(x_k)$ are negative along the entire trajectory;
- then make sure that the function $V(x_k)$ decreases at each step.
4. Results are presented as follows:
- phase trajectories are plotted;
- the total control effort is estimated;
- visualization of system behavior.

Distributed implementation

For a distributed implementation, each subsystem solves its own local optimization problem:

$$J_i(u_i) = \sum_{k=0}^{N-1} \left[V_i(x_i^k) + \rho \left\| x_i^k - \bar{x}_{N_i}^k \right\|^2 + \beta \left\| u_i^k \right\|^2 \right].$$

The coordination mechanism can be implemented in two ways:

1) the Jacobi method: at each iteration, the agent receives data from neighbors and recomputes its control;

2) ADMM: consensus variables and auxiliary Lagrange multipliers are introduced; simplification lies in the fact that the current implementation uses an approximate prototype without multipliers.

This approach provides:

- scalability;
- the ability to add or remove agents without changing the algorithm;
- stability even with incomplete convergence;
- feasibility of application in conditions of limited computing resources.

Empirical verification of the method

Verification objectives and structure

Empirical verification of the method is carried out to confirm its operability and stability in numerical modeling without linearization. The main tasks of verification are:

- confirmation of the correctness of the numerical solution;
- demonstration of a decreasing Lyapunov function along the trajectories;
- verification of consistency and stability in distributed configurations;
- visualization of system trajectories and qualitative interpretation of behavior.

The simulation is implemented using the Python programming language and the numpy, scipy and matplotlib modules. Verification includes two stages:

1) optimization of control on a single system;
2) distributed implementation with multiple agents.

Verification on a single system

System dynamics

The following nonlinear system is considered:

$$\begin{cases} \dot{x}_1 = -x_1 + x_2^2 + u \\ \dot{x}_2 = -x_2 + x_1 x_2 \end{cases}.$$

The Lyapunov function is chosen as:

$$V(x) = x_1^2 + x_2^2.$$

The initial state is set by the following parameters: x_0 = [1,5; –1,0]. Simulation time is T = 10, with a discretization of N = 200.

Without control

Without the control action $u(t) = 0$, the system exhibits unstable behavior. The Lyapunov function does not decrease and sometimes even increases. In the phase plane, the trajectory moves away from the origin.

The Python code to generate the plots (Figs. 1–3) is available for download and can be run locally[1].

Constant optimal control

The problem of finding $u = const$ that minimizes the objective functional for arbitrary control is solved:

$$J(u) = \alpha \int_0^T V(x(t))\,dt + \beta \int_0^T u^2 dt.$$

Substituting the condition $u = const$ into this equation, we obtain:

$$J(u) = \alpha \int_0^T V(x(t;u))\,dt + \beta \int_0^T u^2 dt = \alpha \int_0^T V(x(t;u))\,dt + \beta T u^2,$$

where the trajectory $x(t; u)$ can be expressed by the system:

$$\begin{cases} \dot{x}_1 = -x_1 + x_2^2 + u \\ \dot{x}_2 = -x_2 + x_1 x_2 \\ x(0) + [1.5 - 1.0]^T \end{cases}.$$

At $\alpha = 1$, $\beta = 0{,}1$, the optimal value $u^* \approx -0{,}71$ ensures a guaranteed decrease in $V(x(t))$ and a bounded phase trajectory (the system decays without emissions).

[1] GitHub – fershtadt/lyapunov-control-visualization, Available: https://github.com/fershtadt/lyapunov-control-visualization (Accessed 13.11.2025).

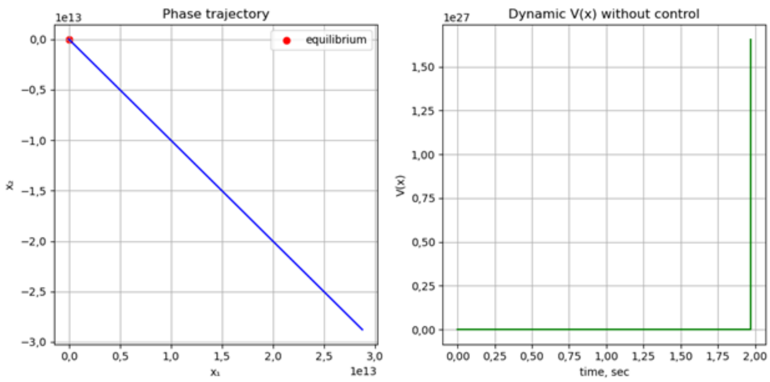

Fig. 1. Simulation of the system without control

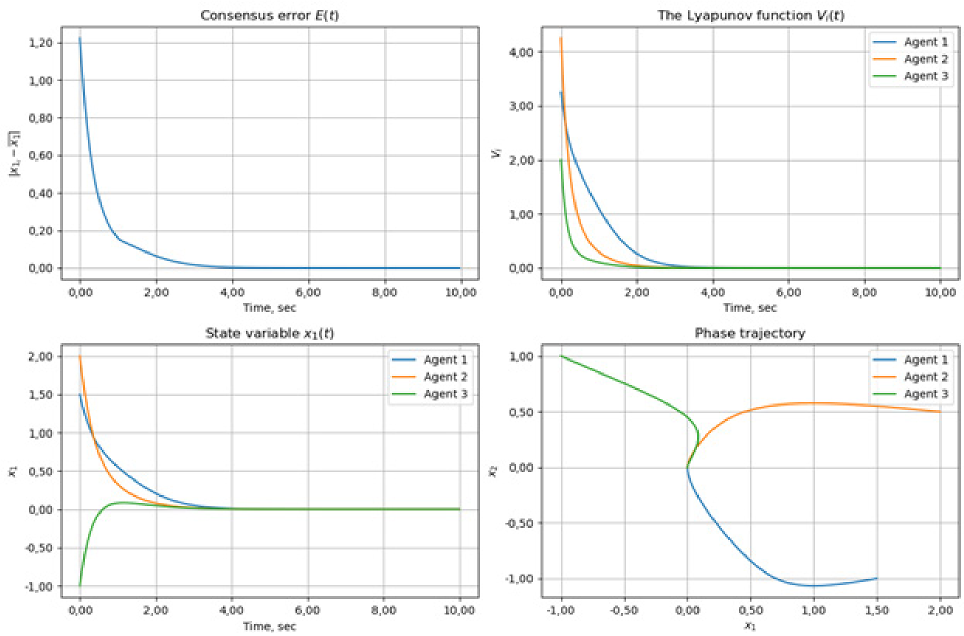

Fig. 2. Simulation with variable control

Variable control

For discrete control u_k ($k = 0, \ldots, N - 1$), the following objective functional is minimized:

$$J(u) = \sum_{k=0}^{N-1} \left[\alpha V(x_k) + \beta u_k^2 \right] \Delta t.$$

Results:

- the Lyapunov function $V(x)$ decreases monotonically;
- trajectories $x_1(t)$, $x_2(t)$ tend to zero without oscillations;
- the derivative $V'(x) < 0$ along the entire trajectory;
- no overflow, oscillations, or anomalies are observed.
- the trajectories $V'(t)$ for each agent lie below zero, therefore, the condition $V' < 0$ along the trajectory is confirmed.

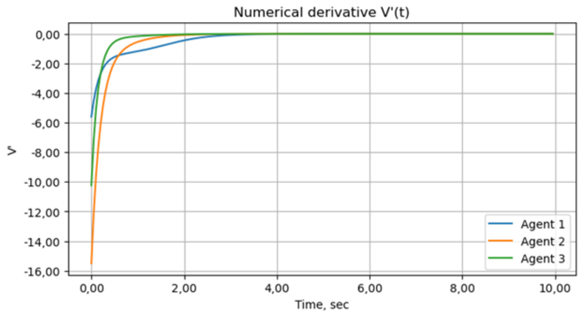

Fig. 3. Numerical derivative of $V(t)$

Conclusions

1. A constant optimal value of u^* stabilizes the system, but the attenuation of $V(t)$ is slower than with an optimized time-varying control strategy.

2. Optimizing the discrete control sequence u_k accelerates convergence and reduces control effort, as evidenced by the steeper decline of $V(t)$ and the negative derivative $V'(t)$ over the entire interval for each agent.

3. It has been empirically confirmed that including the Lyapunov function in the objective vector makes it possible to achieve stability without linearization, even with a simple Euler discretization and a small number of Jacobi coordination iterations.

Verification in a distributed system

System configuration

A system of three agents is being considered:

$$\dot{x}_i = f_i\left(x_i,\ u_i\right) + \sum_{j\in N_i} \gamma_{ij}\left(x_j - x_i\right),$$

where: N_i is the set of neighbors of agent i; $\gamma_{ij} = 0{,}5$ are consensus coefficients.

Each agent has the same local dynamics as the single-system and uses a local control of the form:

$$u_i^k = -Kx_{1,i}^k - \rho\left(x_{1,i}^k - \overline{x}_{1,N_i}^k\right).$$

Distributed optimization

A simulation of distributed coordination using the Jacobi method was implemented in Python (Figs. 2, 3). Each agent updates its trajectory according to its own equations, using the average states of its neighbors.

Jacobi iterations: 20.

Results:

- all agents demonstrate coherent behavior: deviations between them decrease;
- the Lyapunov function decreases for each agent;
- control inputs $u_i(t)$ remain within the acceptable range;
- the agents' phase trajectories converge to a common equilibrium state.

Conclusion

Even in the simplest implementation of distributed optimization (without Lagrange multipliers), the proposed approach provides:

- stability of the entire system;
- coordination between agents;
- numerical stability in nonlinear dynamics.

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