12º CONGRESSO BRASILEIRO DE PESQUISA E DESENVOLVIMENTO EM PETRÓLEO E GÁS

TÍTULO DO TRABALHO:

PREFERENCE-DRIVEN MULTI-OBJECTIVE OPTIMIZATION FOR ENHANCED 3X3 MULTIVARIABLE CONTROLLER TUNING

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Abstract

Multi-objective Optimization Design (MOOD) procedures using Evolutionary Multi-objective Optimization (EMO) are valuable for PID controller tuning, embedding designers in the process to balance conflicting objectives. These procedures involve defining the multi-objective problem (MOP), conducting the EMO process, and multicriteria decision-making (MCDM). Previously, MOOD procedures have been successful in 2x2 multivariable processes, effectively describing trade-offs with the Pareto front. However, complex control problems pose challenges in identifying pertinent solutions due to process complexity and MOP statements. This paper extends MOOD procedures to 3x3 multivariable processes, addressing many-objective optimization instances. It explores incorporating preference handling in EMO to enhance solution pertinency when desirable trade-offs are hard to find. Preference handling focuses algorithms on interesting regions of the objective space, bridging problem definition, optimization, and decision-making processes. This holistic approach helps designers find effective trade-offs in complex processes. This technique combines strengths of different optimization methods to improve convergence and diversity, ensuring meaningful trade-offs for the designer. The aim is to propose a MOOD procedure with preference handling for PID tuning in complex multivariable processes, focusing on a 3x3 configuration to tackle many-objective optimization challenges and achieve effective trade-offs among conflicting objectives.

Palavras-chave: PID Control, multivariable control, multiobjective optimization.

Resumo

Procedimentos de Design de Otimização Multiobjetivo (MOOD) usando Otimização Evolutiva Multiobjetivo (EMO) são valiosos para o ajuste de controladores PID, integrando os designers no processo para equilibrar objetivos conflitantes. Esses procedimentos envolvem a definição do problema multiobjetivo (MOP), a realização do processo EMO e a tomada de decisão multicritério (MCDM). Anteriormente, os procedimentos MOOD foram bem-sucedidos em processos multivariáveis 2x2, descrevendo de forma eficaz as compensações com a frente de Pareto. No entanto, problemas de controle complexos apresentam desafios na identificação de soluções pertinentes devido à complexidade do processo e às formulações do MOP. Este artigo estende os procedimentos MOOD para processos multivariáveis 3x3, abordando instâncias de otimização com muitos objetivos. Explora-se a incorporação do tratamento de preferências no EMO para aumentar a pertinência das soluções quando compensações desejáveis são difíceis de encontrar. O tratamento de preferências foca os algoritmos em regiões interessantes do espaço de objetivos, conectando a definição do problema, a otimização e os processos de tomada de decisão. Esta abordagem holística ajuda os designers a encontrar compensações eficazes em processos complexos. Esta técnica combina as forças de diferentes métodos de otimização para melhorar a convergência e a diversidade, garantindo compensações significativas para o designer. O objetivo é propor um procedimento MOOD com tratamento de preferências para o ajuste de PID em processos multivariáveis complexos, focando em uma configuração 3x3 para enfrentar os desafios de otimização com muitos objetivos e alcançar compensações eficazes entre objetivos conflitantes.

Keywords: Controle PID, controle multivariável, otimização multiobjetivo.

Introduction

PID controllers are widely used in industrial control systems due to their simplicity and effectiveness (Stewart; Samad, 2011). However, tuning these controllers to achieve optimal performance, especially in multivariable processes, presents a significant challenge. Traditional tuning methods often fall short when dealing with multiple conflicting objectives that need to be balanced, such as minimizing overshoot, settling time, and control effort simultaneously. This challenge necessitates more sophisticated approaches that can handle the inherent trade-offs in PID controller tuning.

Multi-objective Optimization Design (MOOD) procedures utilizing Evolutionary Multi-objective Optimization (EMO) have emerged as valuable tools in addressing these challenges Marques; Reynoso-Meza, 2020). These procedures allow designers or decision-makers (DMs) to be actively involved in the design process, evaluating each design objective individually and comparing alternatives to select a controller that best meets the desired trade-offs among conflicting objectives. Traditional MOOD procedures typically involve three fundamental steps: defining the multi-objective problem (MOP), conducting the EMO process, and performing multicriteria decision-making (MCDM).

Previous works have demonstrated the effectiveness of MOOD procedures in multivariable processes with a 2x2 configuration, highlighting their ability to navigate the complex trade-offs required for PID controller tuning (Reynoso-Meza et al., 2016). Despite these successes, more complex control problems, such as those with a 3x3 configuration, pose additional challenges. The complexity of the process and the MOP statement make it difficult to identify a pertinent set of solutions.

To address these challenges, this paper extends the application of MOOD procedures to more complex multivariable processes with a 3x3 configuration, tackling many-objective optimization instances. The paper explores the inclusion of preference handling in the EMO process to enhance the pertinency of solutions when finding a desirable trade-off is challenging. Preference handling directs algorithms to focus on interesting regions of the objective space, effectively integrating problem definition, optimization, and decision-making processes. This holistic approach enables designers to address complex processes more effectively, finding desirable trade-offs among conflicting objectives.

The objective of this paper is to propose a MOOD procedure that incorporates preference handling for PID controller tuning in complex multivariable processes. By focusing on a 3x3 configuration, this research addresses the challenges associated with many-objective optimization instances, providing a robust framework for achieving effective trade-offs among conflicting objectives in PID controller tuning.

The structure of this paper is as follows: Section 2 provides a detailed background and related work on MOOD procedures and EMO techniques. Section 3 outlines the methodology, including the problem definition, EMO process, and preference handling approach. Section 4 presents the experimental setup and results, demonstrating the application of the proposed MOOD procedure to a 3x3 multivariable process. Section 5 discusses the findings and their implications for PID controller tuning. Finally, Section 6 concludes the paper, summarizing the key contributions and suggesting directions for future research.

Methodology

In multivariable control systems, the complexity of managing the interactions between multiple inputs and outputs presents a significant challenge. A basic control loop, may consists of the transfer functions $\mathrm{P}(s)$ and $\mathrm{C}(s)$, representing the process and the controller, respectively. The primary goal of this control loop is to ensure that the process output $\mathrm{Y}(s)$ accurately follows the desired reference $\mathrm{R}(s)$.

When dealing with a $N\times N$ Multiple Input Multiple Output (MIMO) process, the process transfer function $\mathrm{P}(s)$ is composed of several sub-processes $P_{ij}(s)$, where $i,j\in\{1,\ldots,N\}$. This can be represented as follows:

$$\mathrm{P}(s) = \begin{bmatrix} P_{11}(s) & \ldots & P_{1N}(s) \\ \vdots & \ddots & \vdots \\ P_{N1}(s) & \ldots & P_{NN}(s) \end{bmatrix} \tag{1}$$

The inherent complexity in such a system is primarily due to the coupling effects between the various inputs and outputs. Numerous control strategies can be employed to manage a MIMO system, with the choice of method depending on the trade-off between system complexity and the design specifications Proportional-Integral (PI) controllers offer a simple yet effective solution, particularly when augmented by complementary techniques. In this work, we adopt decoupled PI controllers, where the controller $\mathrm{C}(s)$ is structured as follows:

$$\mathrm{C}(s) = \begin{bmatrix} C_1(s) & \ldots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \ldots & C_N(s) \end{bmatrix} \tag{2}$$

Each diagonal element $\mathrm{C_i}(s)$ represents a Single Input Single Output (SISO) PI controller, expressed by the following transfer function:

$$\mathrm{C_i(s)} = \mathrm{k_p}\left(1 + \frac{1}{\mathrm{T_i s}}\right) \tag{3}$$

Here, k_p is the proportional gain, and T_i is the integral time constant. These controllers are tuned to achieve a desirable performance of the process P(s) within the control loop while maintaining robust stability margins.

The tuning of PI controllers in a MIMO context is particularly challenging due to the conflicting objectives that arise from the coupling effects between the sub-processes. Multiobjective Optimization techniques are therefore appealing for this task, as they allow for the simultaneous optimization of multiple conflicting objectives, resulting in a more balanced and effective controller design. For a succesful implementation, three steps are essential: the Multi-objective Problem definition, the multi-objective optimization process and the ulti-criteria decision making/analysis.

Multiobjective Problem Statement

In general, a multi-objective problem can be defined as follows:

$$\min_{\theta} J(\theta) = [J_1(\theta), \ldots, J_m(\theta)] \tag{4}$$

subject to:

$$\mathrm{g}(\theta) \leq 0$$

$$\mathrm{h}(\theta) = 0$$

$$\theta_{\mathrm{max_i}} \leq \theta_\mathrm{i} \leq \theta_{\mathrm{min_i}}, \mathrm{i} = [1, \ldots, \mathrm{n}]$$

where θ is the decision vector, $\mathrm{J}(\theta)$ is the objective vector, $\mathrm{g}(\theta)$ and $\mathrm{h}(\theta)$ are, respectively, the inequality and equality vectors and θ_{max_i}, θ_{min_i} being the boundaries for the decision space for the variable θ_i.

In the work of Reynoso-Meza et al. (2016), a multiobjective problem formulation was proposed, employing preference-based approaches in conjunction with physical programming to approximate the

Pareto front. Although the formulation considered the use of N objectives for performance, N objectives for control action usage, and a global objective for robustness, the integration of preferences facilitated the maintenance of good convergence and diversity properties within the many-objectives environment. However, the decision-making stage was conducted in a space of $2N+1$dimensions.

In this study, we propose an alternative approach by reducing the problem using global physical programming (Reynoso-Meza et al., 2014). One objective aggregates performance indicators using physical programming $\varphi_1(\theta)$, another consolidates control action metrics, $\varphi_2(\theta)$, and the third addresses robustness, $L_{cm}(\theta)$, which is the biggest log modulus used in Luyben (1986). This method tackles the scalability issue inherent in multiobjective optimization problems, ensuring that the optimization problem remains fixed at three objectives. Such a formulation offers a more manageable yet effective solution for addressing the complex trade-offs in MIMO control systems, while maintaining the integrity of the optimization process. That is:

$$\min_{\theta} J\,(\theta) = [\varphi_1(\theta), \varphi_2(\theta), L_{cm}(\theta)] \tag{5}$$

Subject to closed loop stability and boundary constraints.

Multiobjective Optimization Process

In the experiments conducted in this study, we utilized the spMODEx algorithm, a multi-objective evolutionary approach derived from Differential Evolution (Pant et al., 2020). This algorithm incorporates a spherical pruning method as its diversity preservation mechanism. The chosen hyperparameters, following the recommendations of Martinez-Luzuriaga et al. (2023) for the experiments are as follows: binomial mutation, a scaling factor of F=0.5, a crossover rate of Cr=0.9, a population size of Pop=50, a total of 2000 function evaluations, and 100 arcs in the spherical grid.

Multi-criteria Decision Making:

Parallel coordinates will be used to depict the Pareto front approximation. Parallel coordinates are an effective visualization technique for representing high-dimensional data, particularly valuable for visualizing Pareto fronts in multi-objective optimization problems. In this method, each design objective $J_i(\theta)$ is mapped to a vertical axis, where $i \in 1,2,\dots,M$ represents the M objectives being optimized. For a particular solution θ_k, the values of the objectives $J_i(\theta_k)$ are plotted along their respective axes. These values are then connected by a polyline, with each point on the polyline representing the performance of the solution θ_k with respect to each objective.

Results and Discussion

Tests were performed in a Desktop DELL precision 3561, Intel(R) 11th. generation i7-11800H, 2.30 GHz, and 16GB RAM running Matlab R2023b. The following 3x3 MIMO process from the testbed of Luyben (1986) will be used for experimentation:

$$P(s) = \begin{bmatrix} \frac{0.66e^{-2.6s}}{6.7s+1} & \frac{-0.61e^{-3.5s}}{8.64s+1} & \frac{-0.0049e^{-1s}}{9.06s+1} \\ \frac{1.11e^{-6.5s}}{3.25s+1} & \frac{-2.36e^{-3s}}{5s+1} & \frac{-0.01e^{-1.2s}}{7.09s+1} \\ \frac{-34.68e^{-9.2s}}{8.15s+1} & \frac{46.2e^{-9.4s}}{10.9s+1} & \frac{0.87(11.61s+1)e^{-1s}}{(3.89s+1)(18.8s+1)} \end{bmatrix} \tag{6}$$

This process represents a distillation column, a common process in refineries, petrochemical industries, and biofuel production. The experiment for performance measure is a simple reference step change in the first output. In Figure 1, the Pareto front depicting the approximation is exhibited, while in Figure 2 a time performance comparison with the BLT tuning proposed in Luyben (1986) (named as baseline solution). An additional constraint was included to assure that all optimal controllers have the same performance measure as the baseline. As it can be noticed, the Pareto optimal solutions approximated by the proposed approach effectively dominates the baseline solution. The 2-dimensional visualization facilitates any decision making process to select the most preferable solution.

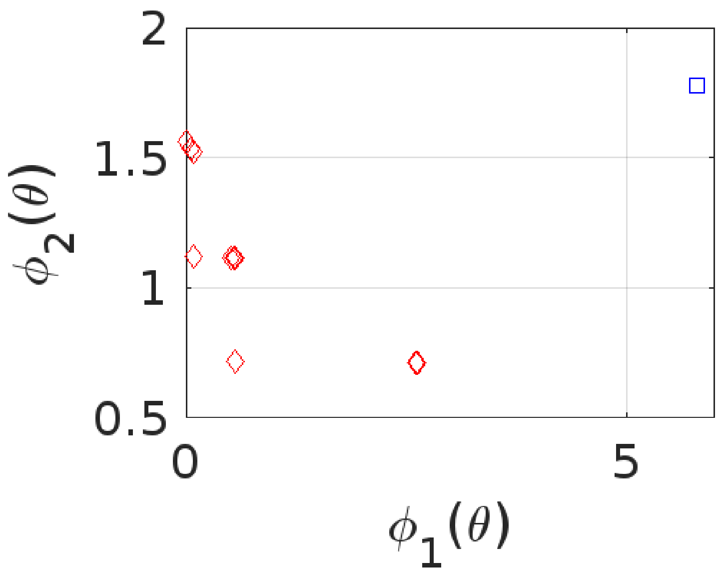

Figure 1. Pareto front approximation (red diamonds) and baseline solution (blue square).

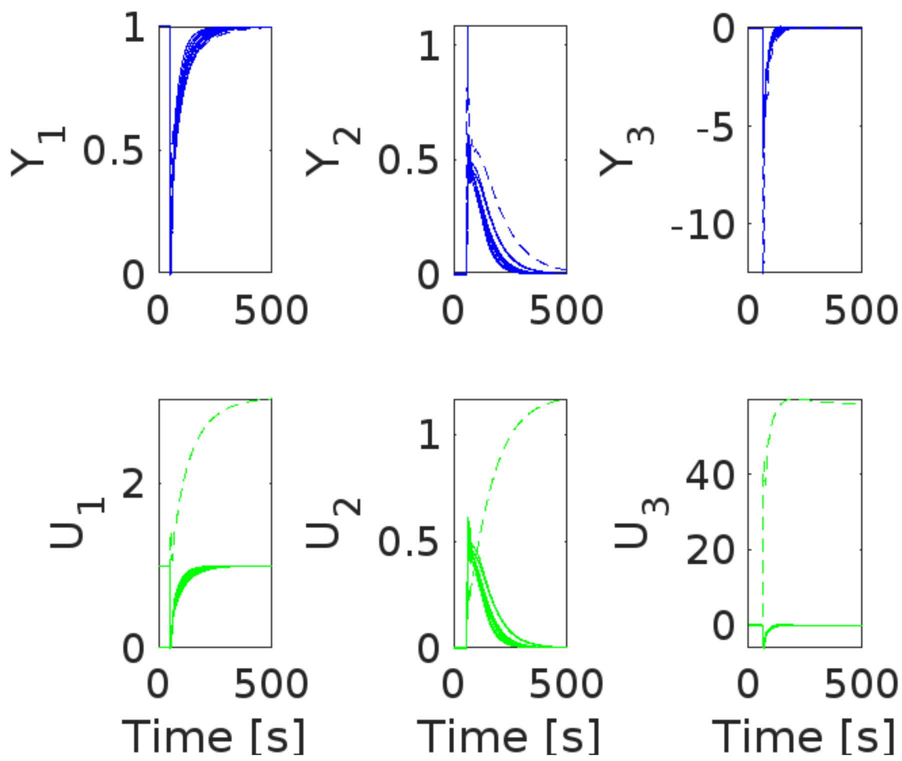

Figure 2. Time response performance. Continuous line represents a Pareto optimal solution of the proposal. Dashed line represents the baseline solution.

Finally, in Figure 3, all design objectives and constraint values are depicted. Such values were normalize using the baseline solution. Therefore, any value below 1 indicates an improvement over this solution. As it can be noticed, an expressive portion of the Pareto optimal solutions approximated dominates the baseline solution.

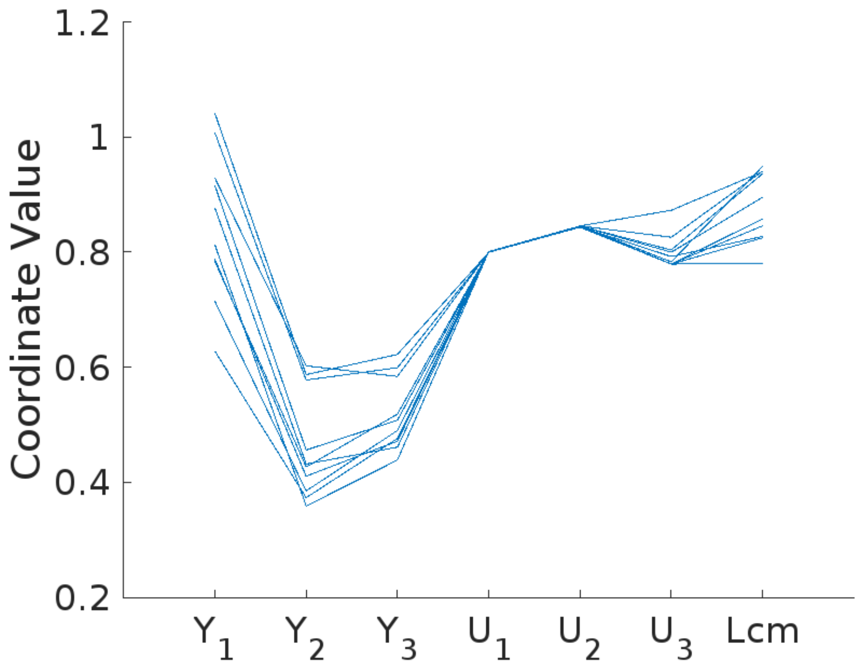

Figure 3. Parallel coordinates visualization of the overall set of design objectives before aggregation via physical programming. All 6design objectives and the constraint has been normalized with the baseline solution. Therefore, any value below 1 improves the baseline.

Conclusions

In this work, a multi-objective optimization scheme has been proposed for 3x3 multivariable control systems. Building on a previous version, which could easily lead to a Many-Objectives Optimization scenario, the current approach aims to mitigate challenges associated with decision-making and potential convergence issues. The proposed methodology introduces a strategy where design objectives are aggregated by category—specifically, performance and control action categories—to streamline the decision-making process.

An experimental evaluation was conducted on a 3x3 plant, demonstrating that the proposed solution framework is capable of generating a Pareto front that not only dominates the base solution in terms of the aggregated objectives but also shows near-dominance when all individual objectives are considered. This suggests that the proposed aggregation method effectively manages the complexity of multi-objective optimization in multivariable control systems.

Future work will focus on extending the experimental framework to higher-dimensional multivariable processes, as well as expanding the experimental base to validate the robustness and generalizability of the proposed approach across a broader range of industrial applications.

Agradecimentos

This study was financed in part by the Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq) via the projects PQ-2/310195/2022-5 & Universal/408164/2021-2.

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