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Tuning of PID controller based on a multiobjective genetic algorithm applied to a robotic manipulator

Helon Vicente Hultmann Ayala [a], Leandro dos Santos Coelho [b,]*

[a] Electricity Department (DPEL), Power Systems Division (DVSE), LACTEC – Institute of Technology for Development, BR 116 KM 98, n. 8813, Zip code 81531-980 Curitiba, Parana, Brazil
[b] Industrial and Systems Engineering Graduate Program, Pontifical Catholic University of Parana, Imaculada Conceicao, 1155, Zip code 80215-910 Curitiba, PR, Brazil

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ABSTRACT

Most controllers optimization and design problems are multiobjective in nature, since they normally have several (possibly conflicting) objectives that must be satisfied at the same time. Instead of aiming at finding a single solution, the multiobjective optimization methods try to produce a set of good trade-off solutions from which the decision maker may select one. Several methods have been devised for solving multiobjective optimization problems in control systems field. Traditionally, classical optimization algorithms based on nonlinear programming or optimal control theories are applied to obtain the solution of such problems. The presence of multiple objectives in a problem usually gives rise to a set of optimal solutions, largely known as Pareto-optimal solutions. Recently, Multiobjective Evolutionary Algorithms (MOEAs) have been applied to control systems problems. Compared with mathematical programming, MOEAs are very suitable to solve multiobjective optimization problems, because they deal simultaneously with a set of solutions and find a number of Pareto optimal solutions in a single run of algorithm. Starting from a set of initial solutions, MOEAs use iteratively improving optimization techniques to find the optimal solutions. In every iterative progress, MOEAs favor population-based Pareto dominance as a measure of fitness. In the MOEAs context, the Non-dominated Sorting Genetic Algorithm (NSGA-II) has been successfully applied to solving many multiobjective problems. This paper presents the design and the tuning of two PID (Proportional–Integral–Derivative) controllers through the NSGA-II approach. Simulation numerical results of multivariable PID control and convergence of the NSGA-II is presented and discussed with application in a robotic manipulator of two-degree-of-freedom. The proposed optimization method based on NSGA-II offers an effective way to implement simple but robust solutions providing a good reference tracking performance in closed loop.

1. Introduction

The desired goals in modern control engineering design can be addressed as the resolution of an optimization problem. In general, the state problem is defined as a single objective function expressed as a mathematical function based on some criteria. In many cases, a designer needs to make tradeoffs between disparate and conflicting design objectives. At this point, the definition of a multiobjective optimization (MO) problem can be interesting, given that the field of MO defines the art and science of making such decisions. The MO techniques offer advantages when compared with single objective optimization techniques because they may produce a solution with different trade-offs among different individual objectives, so that the designer can select the best final solution (Martínez, García-Nieto, Sanchis, & Blasco, 2009).

Generally speaking, MO does not restrict to find a unique single solution of a given problem, but a set of solutions called *non-dominated solutions*. Each solution in this set is said to be a *Pareto optimum*, and when they are plotted in the objective space they are collectively known as the *Pareto front*. Obtaining the Pareto front of a given MO problem is the main goal of multiobjective optimization. In this context, Pareto optimality is a measure of efficiency in multicriteria and multiobjective situations.

Most optimization problems in control systems involve the optimization of more than one objective function (Aggelogiannaki, Sarimveis, & Bafas, 2004; Ayala & Coelho, 2008; Carvalho & Ferreira, 1995; Liao & Li, 2002; Liu & Wang, 2000; Serra & Bottura, 2006; Zambrano & Camacho, 2002), which in turn can require a significant computational time to be evaluated. In this context, deterministic techniques are difficult to apply to obtain the set of Pareto optimal solutions of many multiobjective optimization problems,

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* Corresponding author. Tel.: +55 41 3271 13 33; fax: +55 41 3271 13 45.
E-mail addresses: hvha@ieee.org (H.V. Hultmann Ayala), leandro.coelho@pucpr.br (L. dos Santos Coelho).

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so stochastic methods have been widely used and applied. Among them, the use of evolutionary algorithms and other nature-inspired algorithms for solving multiobjective optimization problems has significantly grown in the last years, giving raise to a wide variety of algorithms (Coello, 1999; Coello, Van Veldhuizen, & Lamont, 2002; Deb, 2001; Fonseca & Fleming, 1995; Osyczka, 1985; Van Veldhuizen & Lamont, 2000). Evolutionary Algorithms (EAs) are general-purpose stochastic search methods that use the metaphor of evolution as the key element in the design and implementation of computer-based problem solving systems. EAs offer a number of advantages: robust and reliable performance, global search capability, little or no information requirement, and others.

In recent years, in particular, genetic algorithms (GAs) have been investigated by many authors (see examples in Amjady & Nasri-Rad (2010), Bakirli, Birant, & Kut (2011), Coello (1999), Coello et al. (2002), Deb (2001), Kuroki, Young, & Haupt (2010), Lee & Ahn (2011), Mahmoudabadi & Tavakkoli-Moghaddam (2011), Prakash, Chan, & Deshmukh (2011)). GAs are based on the genetic process of biological organisms such as natural selection and reproduction. Furthermore, GAs are adaptive methods that may be used to solve search and optimization problems. GAs do not guarantee to obtain the optimal solution, but they provide appropriate solutions to a wide range of optimization problems which other deterministic methods find difficult. However, GA possesses advantages that it does not require any gradient information and inherent parallelism in searching the design space, thus making it a robust adaptive optimization technique.

GAs work with a population of individuals (potential solutions of optimization problem), each representing a possible solution to a given problem. Each individual is assigned a fitness score according to the qualification of that solution for the given problem. Individuals are selected from the population and recombined to produce offspring (new solutions) using the crossover and mutation mechanisms comprising the next generation. The GA is applied until that the evolutionary procedure meets a given evolution stopping criteria.

For multi-objective optimization methods, some modification to the simple GA is necessary. Multi-Objective Genetic Algorithm (MOGA) (Fonseca & Fleming, 1993), Vector Evaluated Genetic Algorithm (VEGA) (Schaffer, 1985), Niched Pareto Genetic Algorithm (NPGA) (Horn, Nafpliotis, & Goldberg, 1994) and Non-Dominated Sorting Genetic Algorithm (NSGA) (Srinivas & Deb, 1994) are examples of GA based multi-objective solution methods.

The NSGA proposed by Srinivas and Deb (1994) has been successfully applied to solving many problems, the main criticisms of this approach has been its high computational complexity of nondominated sorting, lack of elitism, and need for specifying a tunable parameter called sharing parameter. Recently, Deb, Pratap, Agarwal, and Meyarivan (2002) reported an improved version of NSGA, which they called NSGA-II, to address all the above issues. NSGA-II is based on Pareto solutions, measuring individual fitness according to their dominance property. The non-dominated individuals in the population are regarded as the fittest, and the dominated individuals are assigned lower fitness values.

The purpose of this work is to extend this methodology for solution of a multiobjective control problem under the framework of NSGA-II approach proposed in Ayala and Coelho (2008). The efficiency of the proposed method is illustrated by solving the tuning of a PID (Proportional-Integral-Derivative) multivariable controller applied to a robotic manipulator of two-degree-of-freedom. In the present work, two objective optimizations were carried out to obtain the PID's design parameters. Simulation results show that the NSGA-II algorithm can evolve good control profiles which result in an acceptable compromise between two (and possibly conflicting) objectives of tracking of position and velocity trajectories.

The remainder of this paper is organized as follows. In Section 2, the fundamentals of robotic manipulator are presented, while Section 3 explains the concepts of multiobjective optimization and the NSGA-II method. Section 4 presents the setup the NSGA-II approach and the simulation results. Lastly, Section 5 outlines the conclusion and future research.

2. Description of robotic manipulator of two-degree of freedom

Equations that characterize the robot dynamic are represented by a set of coupling differential equations, and, there are terms such as: varying inertia, centrifugal and Coriolis torques, load and gravity terms. The movement of the end-effector in a particular trajectory with constraint speed requires a complex set of torque functions to be applied to the actuators in the link of the robotic manipulator. Next, the description of the robot mathematical model is presented.

The manipulator model usually considers the representation of the robotic manipulator dynamic of n-links (in our case $n = 2$) governed by the following equation (Ayala & Coelho, 2008):

$$M(\theta)\ddot{\theta} + C(\theta,\dot{\theta}) + G(\theta) = \tau \tag{1}$$

where $M(\theta) \in \Re^{nxn}$ is the positive definite matrix of the system, $C(\theta,\dot{\theta}) \in \Re^{nx1}$ is the vector that represents the effects of centrifugal and Coriolis torques, $G(\theta) \in \Re^{nx1}$ is the vector of the gravitational torque effect, $\tau \in \Re^{nx1}$ is the vector of the torque of the links, and, $\theta, \dot{\theta}$, and $\ddot{\theta}$ are angular position, velocity and acceleration of the links. The dynamic model of robotic manipulator utilized for evaluation of the controllers is presented in Fig. 1.

The dynamic equations are given by Craig (1996):

$$\begin{aligned}\tau_1 = {} & m_2 l_2^2(\ddot{\theta}_1 + \ddot{\theta}_2) + m_2 l_1 l_2 c_2(2\ddot{\theta}_1 + \ddot{\theta}_2) + (m_1 + m_2) l_1^2 \ddot{\theta}_1 \\ & - m_2 l_1 l_2 s_2 \dot{\theta}_2^2 - 2 m_2 l_1 l_2 s_2 \dot{\theta}_1 \dot{\theta}_2 + m_2 l_2 g c_{12} + (m_1 + m_2) l_1 g c_1\end{aligned} \tag{2}$$

$$\tau_2 = m_2 l_1 l_2 c_2 \ddot{\theta}_1 + m_2 l_1 l_2 s_2 \dot{\theta}_1^2 + m_2 l_1 g c_{12} + m_2 l_2^2(\ddot{\theta}_1 + \ddot{\theta}_2) \tag{3}$$

where $s_1 = \sin(\theta_1)$, $s_2 = \sin(\theta_2)$, $c_1 = \cos(\theta_1)$, $c_2 = \cos(\theta_2)$, and $c_{12} = \cos(\theta_1 + \theta_2)$ and the subscript 1 and 2 denote the parameters of the links 1 and 2, respectively. Parameters utilized in all simulations were: links lengths — $l_1 = 0.8$ m and $l_2 = 0.4$ m, links masses — $m_1 = m_2 = 0.1$ kg, and gravity acceleration $g = 9.81$ m/s^2 (Mital & Chin, 1995). The sampling period is $T_s = 10$ ms and the simulation period is 2 s ($N = 200$ samples). The imposed constraint in torque τ_1 and τ_2 are $[-1000; 1000]$ N m. Signals $\theta_{d,j}$ and $\dot{\theta}_{d,j}$ are desired values of the angular position and velocity of the robotic links, respectively. The position and velocity error vectors are respectively defined by

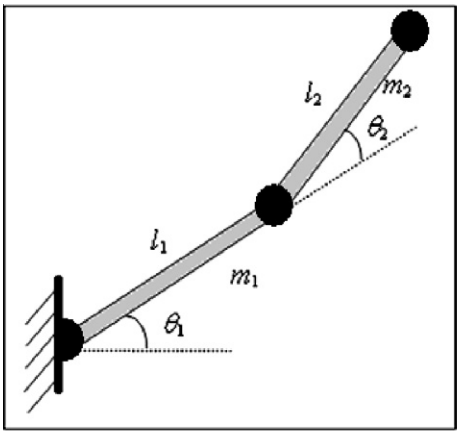

Fig. 1. Geometry of robotic manipulator of two-degree of freedom.