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Quasi-LPV modeling, identification and control of a twin rotor MIMO system

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ABSTRACT

This paper describes the quasi-linear parameter varying (quasi-LPV) modeling, identification and control of a Twin Rotor MIMO System (TRMS). The non-linear model of the TRMS is transformed into a quasi-LPV system and approximated in a polytopic way. The unknown model parameters have been calibrated by means of the non-linear least squares identification approach and validated against real data. Finally, an LPV state observer and state-feedback controller have been designed using an LPV pole placement method based on LMI regions. The effectiveness and performance of the proposed control approach have been proved both in simulation and on the real set-up.

1. Introduction

This paper describes the quasi-linear parameter varying (quasi-LPV) modeling, identification and control of the twin rotor multiple-input multiple-output system (TRMS), developed by Feedback Instruments Limited for control experiments. This system resembles a simplified behavior of a conventional helicopter with less degrees of freedom (DOF). The system is perceived as a challenging engineering problem owing to its high non-linearity, cross-coupling between its two axes, and inaccessibility of some of its states for measurements.

An attractive solution to represent non-linear systems are LPV models. The main advantage of LPV models is that they allow applying powerful linear design tools to complex non-linear models (Reberga, Henrion, Bernussou, & Vary, 2005; Rodrigues, Theilliol, Aberkane, & Sauter, 2007; Wan & Kothare, 2003). LPV control synthesis fits into the gain-scheduling framework, while adding stability and robustness guarantees. The strength of the LPV approach lies in the extension of well-known methods for linear optimal control, including the use of linear matrix inequalities (LMIs), to the design of gain-scheduled LPV controllers. A condition to apply LPV control synthesis is to transform the non-linear model of the system into an LPV model; hence, LPV modeling becomes a key issue in the design of LPV controllers (Andrés & Balas, 2004; Papageorgiou, 1998; Shamma & Cloutier, 1993). Luckily, many non-linear systems of practical interest can be represented as quasi-LPV systems, where *quasi* is added because the scheduling parameters do not depend only on external signals, but also on system variables (Kwiatkowski, Boll, & Werner, 2006). For further information about LPV systems, see Rugh and Shamma (2000), Toth, Abbas, and Werner (2012) and the references therein.

The first development of LPV model identification methods focused on a global procedure, resulting in techniques that identify LPV models based on *one* set of measurements on the system with time-varying parameters. These techniques assume that one global experiment was enough to excite both the control inputs and the scheduling parameters (Lee & Poolla, 1999; Nemani, Ravikanth, & Bamieh, 1995; van Wingerden & Verhaegen, 2009). On the other hand, more recently, techniques that identify LPV models based on different sets of system measurements for different frozen values of the varying parameter have been investigated (Groot Wassink, van de Wal, Scherer, & Okko Bosgra, 2005; Paijmans, Symens, Van Brussel, & Swevers, 2008; Steinbuch, van de Molengraft, & van der Voort, 2003; van Helvoort, Steinbuch, Lambrechts, & van de Molengraft, 2004). These techniques start from a set of LTI identifications based on system measurements for a set of frozen values of the scheduling parameters. By interpolating between these local LTI models an LPV model is obtained.

In the last decade, the modeling and experimental identification of the TRMS have been investigated and addressed in many papers. Radial basis function networks were used in Ahmad, Shaheed, Chipperfield, and Tokhi (2000), where a non-linear modeling and identification approach was presented and applied to air vehicles of complex configuration. In Ahmad, Chipperfield, and Tokhi (2002), a black-box system identification technique

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was used to obtain a dynamic model for a 1DOF TRMS in hover. In Darus, Aldebrez, and Tokhi (2004), genetic algorithms based on one-step-ahead prediction were used to identify the parameters of the TRMS in hovering position. Shaheed (2004) obtained a model of the TRMS using a non-linear autoregressive process with external input (NARX) paradigm with a feedforward neural network. In Aldebrez, Darus, and Tokhi (2004), the utilization of neural networks and parametric linear approaches for modeling a TRMS in hovering position has been investigated. In Alam and Tokhi (2007), particle swarm optimization is used to model the TRMS. First, 1DOF models are extracted for both vertical and horizontal channels, respectively. Then, a 2DOF parametric model is developed taking into consideration cross-couplings between the channels. In Rahideh and Shaheed (2007), the system is modeled in terms of vertical 1DOF, horizontal 1DOF and 2DOF dynamics using Newtonian as well as Lagrangian methods. Further improvements of such model can be found in Gabriel (2008), Nejjari, Rotondo, Puig, and Innocenti (2011), and in Rahideh, Shaheed, and Huijberts (2008), where, in addition, Levenberg–Marquardt and gradient descent neural network-based empirical models are obtained and compared to the Newtonian and Lagrangian analytical ones. In Toha and Tokhi (2009), the parametric modeling of the TRMS is obtained by means of real-coded genetic algorithm. In Toha and Tokhi (2010a), an adaptive neuro-fuzzy inference system tuned by a particle swarm optimization algorithm is developed in search for a non-parametric model of the TRMS. In Toha and Tokhi (2010b), a fourth-order linear auto-regressive moving average model that describes the hovering motion of the TRMS is obtained by means of recursive least squares, genetic algorithms and particle swarm optimization.

Regarding the control of the TRMS, a non-linear predictive control has been presented in Dutka, Ordys, and Grimble (2003). The non-linearity is handled by converting the state-dependent state-space representation into the linear time-varying representation. In López-Martinez and Rubio (2003) and López-Martinez, Díaz, Ortega, and Rubio (2004), the control of the twin rotor system using feedback linearization techniques (as full state linearization and input output linearization) has been suggested. In López-Martinez, Ortega, and Rubio (2003), a H_∞ controller for helicopter dynamics is proposed. Later, a non-linear H_∞ approach for handling the coupling considered as a disturbance that should be rejected is introduced in López-Martinez, Vivas, and Ortega (2005). The resulting controller exhibited attributes of a non-linear PID with time-varying constants according to the operating point. In Ahmed, Bhatti, and Iqbal (2009), a sliding mode control by defining a sliding surface that allows to deal with cross-coupling inherent in the twin rotor dynamics is considered. In Rahideh and Shaheed (2009), the TRMS is controlled using robust model predictive control based on polytopes. In Tao, Taur, Chang, and Chang (2010), a fuzzy-sliding and fuzzy-integral-sliding controller is designed to position the yaw and pitch angles of a TRMS.

The interest in LPV systems is motivated by their use in gain-scheduling control techniques. The possibility to embed non-linear systems into the LPV framework, by hiding non-linearities within the scheduling parameter, enables the application of linear-like control methods to non-linear systems such that, at the same time, stability and desired performance of the closed-loop system are guaranteed.

The work presented in this paper is an improvement and an extension of Nejjari et al. (2011) and Nejjari, Rotondo, Puig, and Innocenti (2012). In Nejjari et al. (2011), the model proposed by Rahideh and Shaheed (2007) was used as a starting point for obtaining a quasi-LPV representation of the TRMS to be used for the design of a state observer and a state-feedback controller. The proposed modeling and control approach was tested in simulation in order to prove its effectiveness and performance. In Nejjari et al. (2012), the parameters of the non-linear model were calibrated using data collected from the real lab set-up. The obtained model was used to derive a polytopic model that could be used for controlling the real set-up. In this paper, the modeling and identification techniques described in Nejjari et al. (2012) are used to obtain a polytopic model for a real TRMS. This model is used for controlling the real TRMS, thus showing that the approach proposed in Nejjari et al. (2011) can be successfully applied in practical control problems. In the current paper, the whole procedure is discussed in a more detailed and integrated way such that this paper could be used as a guide for solving the full LPV modeling/identification/control approach for the TRMS system, that can be extended to the control of other complex non-linear systems.

One of the contributions of this paper is the improvement of the non-linear model of the TRMS proposed by Rahideh and Shaheed (2007) taking into account some coupling phenomena that were noticed during the identification process. Another contribution is the proposition of a way that permits transforming the TRMS non-linear model into a discrete-time polytopic quasi-LPV model. The method presented in Kwiatkowski et al. (2006) for an automated generation of affine LPV representations from non-linear and parameter dependent systems is used. Including the TRMS model non-linearities in an LPV framework leads to an improvement in the modeling accuracy and control performance of such a system. The resulting model is polytopic and quasi-LPV, and is used directly in the control strategy. Another contribution consists in using the so called *glocal* identification procedure (Mercere, Lovera, & Laroche, 2011), to estimate a global quasi-LPV model of the TRMS from local experiments. Once the model is identified, the LPV control theory developed by Apkarian, Gahinet, and Becker (1995) is applied. This control methodology allows designing an LPV state-feedback controller that automatically adapts to the operating point. Since not all the TRMS state variables are measured, an LPV state observer is designed to estimate them. Finally, an important practical contribution of this work is the application of the proposed LPV modeling, identification and control approach to the real TRMS system. It should be stated that the Takagi–Sugeno (TS) modeling and control paradigm (Takagi & Sugeno, 1985) could alternatively be used for the control of the TRMS. According to Mäkilä and Viljamaa (2002), Bergsten, Palm, and Driankov (2002) and Rong and Irwin (2003), polytopic LPV models and TS models are very similar and probably the results obtained when applied to the TRMS would be very close.

The structure of the paper is the following: In Section 2, the Twin-Rotor MIMO System is described and its mathematical model is provided. In Section 3, a method for the automated generation of LPV models is applied so as to obtain the quasi-LPV model of the TRMS and the *bounding box* method is used to get a polytopic quasi-LPV representation that can be used for design purposes. Section 4 describes the identification approach used to estimate the unknown parameters of the TRMS model. Section 5 reviews the background on LPV control design using LMI pole placement and presents the design of the LPV state-feedback controller and state observer. Finally, the TRMS identification and control results are shown in Section 6 and the main conclusions are summarized in Section 7.

1.1. Nomenclature

Given a vector $\boldsymbol{v} \in \mathbb{R}^{n_v}$, its ith element is denoted by v_i, with $i = 1, \ldots, n_v$. In case a lower and upper bound for v_i are known,