

**A Multi-Criteria Optimization Framework for
Interaction Controller Design for
Physical Human-Robot Interaction**

by

Yusuf Aydın

A Dissertation Submitted to the
Graduate School of Sciences and Engineering
in Partial Fulfillment of the Requirements for
the Degree of

Doctor of Philosophy

in

Mechanical Engineering



February 20, 2019

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Interaction Controller Design for Physical Human-Robot Interaction**

Koç University

Graduate School of Sciences and Engineering

This is to certify that I have examined this copy of a doctoral dissertation by

Yusuf Aydın

and have found that it is complete and satisfactory in all respects,
and that any and all revisions required by the final
examining committee have been made.

Committee Members:

Prof. Dr. Çağatay Başdoğan (Advisor)

Assoc. Prof. Dr. Volkan Patoğlu (Co-advisor)

Prof. Dr. Hakan Temeltaş

Assoc. Prof. Dr. Erhan Öztop

Assoc. Prof. Dr. İpek Başdoğan

Asst. Prof. Dr. Mehmet Berke Gür

Date: _____



To my beloved family

ABSTRACT

In the near future, humans and robots are expected to perform collaborative tasks involving physical interaction in various environments, such as homes, hospitals, and factories. Robots are good at precision, strength, and repetition, while humans are better at adaptation and cognitive tasks. Physical human-robot interaction (pHRI) takes advantage of both robots and humans to improve speed, flexibility, and ergonomics of complex tasks. pHRI requires design of controllers to achieve safe and transparent operations which is challenging mainly due to the contradicting nature of these objectives. Knowing that attaining perfect transparency is practically unachievable, controllers allowing better compromise between these objectives are desirable.

In the first part of this dissertation, we propose a new controller, fractional order admittance controller, for pHRI. The stability and transparency analyses of the new control system are performed computationally with human-in-the-loop. Impedance matching is proposed to map fractional order control parameters to integer order ones to enable comparisons, and the stability robustness of the system is studied analytically. Furthermore, the interaction performance is investigated experimentally through two human subject studies involving continuous contact with linear and nonlinear viscoelastic environments. The results indicate that the fractional order admittance controller can be more robust and transparent than the integer order admittance controller and the use of fractional order term can reduce the human effort during tasks involving contact interactions with environment.

In the second part of this dissertation, we propose a multi-criteria optimization framework for interaction controller design, which jointly optimizes the stability robustness and transparency of a closed-loop pHRI system for a given interaction controller structure. In particular, we propose a Pareto optimization framework that allows the designer to make informed decisions by studying the tradeoff between stability robustness and transparency

thoroughly. The proposed framework involves a search over the discretized controller parameter space to compute the performance metrics. Using multi-criteria optimization, Pareto front curve depicting the tradeoff between stability robustness and transparency is obtained. Studying this tradeoff, an informed decision can be made to select the set of controller parameters that yield maximum attainable transparency and stability robustness. To demonstrate the practical use of the proposed design approach, integer and fractional order admittance controllers are studied as a case study and compared both analytically and experimentally. Experimental comparisons are performed for a pHRI task that involves contact interactions with an environment displaying nonlinear stiffness. The results validate the proposed design framework, and show that the achievable transparency under fractional order admittance controller is higher than that of integer order one, when both controllers are designed to ensure the same level of stability robustness.

ÖZETÇE

Yakın gelecekte ev, hastane, fabrika gibi çeşitli ortamlarda, insanların ve robotların birlikte fiziksel işbirliğine dayalı ortaklaşa işler yapması beklenmektedir. İnsanlar, üstün zihinsel yeteneklere sahip iken, robotlar dayanıklılık, konumlamadaki yüksek doğruluk ve tekrarlanabilirlik gibi konulardaki avantajlarıyla ön plana çıkarlar. Fiziksel insan-robot işbirliği sayesinde insanların ve robotların yetenekleri bir araya getirilerek karmaşık görevlerin yürütülmesi sırasında hız, esneklik ve ergonomi açılarından iyileşmeler sağlanabilir. Fiziksel insan-robot işbirliği, birbirleriyle çelişen yapılarda olan yüksek şeffaflık ve yüksek güvenlik hedeflerinin aynı anda gerçekleşmesini gerektirmektedir ve bu durum araştırmacılar için zor bir denetim problemidir. Mükemmel şeffaflık pratikte erişilemez olduğu için bu hedefler arasında en iyi ödünleşime izin veren denetleyiciler tercih edilmektedir.

Bu tezin ilk kısmında, fiziksel insan-robot etkileşimi için yeni bir denetleyici mimarisi olarak kesir dereceli admitans denetleyicileri öneriyoruz. Önerilen denetleyiciyi içeren sistemin kararlılık ve şeffaflık çözümlemeleri, insan da döngü içine dahil edilerek yapılmıştır. Kesir dereceli denetleyicinin değişkenlerini tam sayılı denetleyici değişkenlerine eşleştirmek için empedans eşleme yöntemi önerilmiş ve bu sayede sistemlerin gürbüz kararlılığı analitik olarak karşılaştırılmıştır. Ayrıca, etkileşim başarımı, insan deneklerin katıldığı doğrusal olan ve olmayan çevrelerle temas içeren iki farklı deneysel çalışma ile incelenmiştir. Sonuçlar, fiziksel etkileşimde kesir dereceli admitans denetleyicileri kullanıldığında tam sayı dereceli olanların kullanımına göre daha fazla gürbüzlük ve şeffaflığa erişilebileceğini göstermiş, denetleyicideki kesir dereceli terimin çevre ile temas içeren etkileşim görevlerinde insanın harcadığı eforu azalttığını dair kanıtlar sunulmuştur.

Tezin ikinci kısmında, belirli bir etkileşim denetleyici yapısı için, kapalı çevrim fizik-

sel insan-robot etkileşim sisteminin şeffaflığını ve gürbüz kararlılığını birlikte en iyileyecek çok kriterli bir optimizasyon çerçevesi önerilmiştir. Önerdiğimiz Pareto optimizasyon çerçevesi, şeffaflık ve gürbüz kararlılık arasındaki ödünleşimi kapsamlıca inceleyip, tasarımcının ödünleşim hakkında yeterli bilgiye ulaştıktan sonra bilgiye dayalı karar vermesini sağlamaktadır. Bu yapı, gürbüz kararlılık ve şeffaflık için tanımlanmış performans ölçütlerinin (amaç fonksiyonlarının) ayrıklaştırılmış denetleyici değişken uzayında hesaplanmasını içermektedir. Çok kriterli optimizasyon kullanılarak elde edilen Pareto cephesi eğrisi, şeffaflık ve gürbüz kararlılık arasındaki ödünleşimi tarif etmektedir. Bu ödünleşim çalışılarak, ulaşılacak en yüksek şeffaflık ve gürbüz kararlılığı sağlayacak denetleyici değişken kümesi bilinçli şekilde seçilebilir. Önerilen tasarım yönteminin pratik kullanımını göstermek için tam sayılı ve kesir dereceli admitans denetleyiciler örnek olarak çalışılmış, bu iki denetleyici mimarisinde yapılan tasarımlar teorik ve deneysel olarak karşılaştırılmıştır. Deneysel kıyaslamalar, esnekliği doğrusal olmayan bir çevre ile temas içeren fiziksel insan-robot ortaklaşa görevi sırasında yapılmıştır. Sonuçlar, önerilen tasarım çerçevesinin geçerliliğini doğrulamaktadır ve ayrıca, iki denetleyici sistemin gürbüz kararlılığı aynı olacak şekilde tasarlandığında, kesir dereceli admitans denetleyicinin tam sayılı olana göre daha fazla şeffaflık sağlayabileceğini ortaya koymaktadır.

ACKNOWLEDGMENTS

First of all, I would like to express my sincere and deepest gratitude to my advisors Prof. Çağatay Başdoğan and Prof. Volkan Patoğlu for their support, valuable criticism, guidance, endless patience, motivation, encouragement, and enthusiasm throughout my study. I want to thank Prof. Çağatay Başdoğan for his work and dedication to research. He has been a great mentor to me. He has taught me a great deal about professionalism. I am sure that my research skills are amplified thanks to him and I also hope that one day, I will reach his level of writing and presentation skills at least to some extent. I want to thank Prof. Volkan Patoğlu for his endless effort and time that he spent for me and our research. His contributions, positive feedback he provided (even at late night), the momentum and spin that he put to this research will always be remembered and appreciated. I cannot imagine this dissertation without his critical touch. I have learned and gained a lot, thanks to him.

I would like to also express my gratitude to Prof. Erhan Öztop and Prof. İpek Başdoğan for being in the thesis monitoring committee and for their valuable criticism, suggestions, and guidance for my dissertation. I would like to thank Prof. Sandra Hirche for the effort she put during my thesis topic proposal, Prof. Hakan Temeltaş and Prof. Berke Gür for their precious time they spent during my thesis defense and for their valuable criticism, suggestions, and guidance.

I am deeply indebted to Dr. Ozan Tokatlı. He has contributed tremendously to every line of this dissertation, from the idea to results and published papers. He is a colleague and a dear friend to me so that I can always rely on him. I hope we will have more chances in the future to work together again.

I would like to thank Prof. Barış Akgün for his support and guidance to me. His suggestions, ideas, and confidence have always motivated me both for my research and future career.

I would like to thank Ozan Çaldıran. I want to acknowledge that this study would not have begun without his critical touch at the right moment. I am genuinely grateful to him for guidance and support. If the discussions we made throughout my studies were not to happen, this dissertation could not have been completed.

I would like to thank Prof. Ayse Kucukyilmaz. She is and always will be one of the great people that I am happy to work with, meet, and know. I will never forget her support and advice regarding my career and many shared memories and discussions.

I want to thank Arda Aytekin, Ph.D. I don't know where to start to talk about him. He is always the person who helped everybody around him. If his help, motivations, and interventions haven't occurred, probably, today I would not be able to defend my thesis. All my desperate times related to my research or my problems about life, he was always there to talk. Although he was graduated and went abroad for his Ph.D. studies, he has still been dealing with my ridiculous problems. Thank you, Arda.

My dear friend for 17 years now, my flat-mate, my colleague, Gökhan Nadar, I don't know how to thank him. He has always been there for me, and I am sure he will still be. His especially moral support in every problem that I encountered will never be forgotten. Also, I will always remember the times that we studied to solve unbearable engineering problems together. He is the person who took me from the deep of the ocean and brought me back to the surface in the most desperate moments of mine.

I would like to thank Çağrı Yeşil. He was always a big brother and a dear friend to me since I met him. I will never forget and always appreciate what he has taught me. So, I am genuinely grateful to him. Regardless of where and whom he is with, he repeatedly made his best to assist me for essentials of coding and algorithms, and debug my routines through his cell phone. He never gave up on me at any time.

I would like to thank Prof. Mehmet Ayyıldız who is a great friend to me and somebody to always rely on. During his Ph.D. studies, he has always been a big brother and a dear friend to me, and I will never forget what he has taught and suggested to me. Also, I would like to thank Senem Ezgi Emgin for her support and motivation. Moreover, without her

effort and coding skills, I could never complete the critical tasks. I want to express my gratitude to them as well as my friends and colleagues Dr. Gökhan Serhat, Dr. Ömer Şirin, Dr. Utku Boz, and Dr. Yasemin Vardar for always doing their best for me and I would like to mention the precious times we have shared.

I want to thank Doğanay Şirintuna, Utku Erdem, Yahya Al-Qaysi for being companions for me during the last couple of years of my studies. I cherished our discussions and would like to express how much they added to me. In particular, Utku helped me almost more than he could, and I have had joy working together with him for the last two years.

I would like to thank Dr. Bora Karasulu for his friendship. Also, I want to thank Hatice and İsmail Menekşe for their kindness and the warm ambient they have provided. I would like to thank Muzaffer Bütün for the practical solutions he offered, and all the assistance whenever I needed. It was a privilege to know and share time with my colleagues Ayberk Sadiç, Aykut İşleyen, Bushra Sadia, Cem Eteke, Doğançan Kebüde, İdil Özdamar, Khurram Saleem, Mahmut Biçer, Milad Jamalzadeh, Mustafa Yılmaz, Zaid Al-Saadi.

I would like to thank Şilan Can Gökçe for being able to put up with never-ending working hours and fatigue, and trying to help me more than she can. I cannot imagine either this period or any future moments of my life without her.

I wish my grandfather could be here to witness this moment. He had tremendous confidence in me to do the right things. I believe his soul rests in peace.

Last but not least, I want to thank my entire family and especially my father, my mother, and my elder and little brothers, and my sister. They always believed in me and supported me through my studies and my life. Sometimes they had their doubts about what I am going to do, but they have always helped me to decide. When I had any problems in my life to solve and any happiness to share, I hope, and I am sure that they will still be there for me.

I want to express my gratitude to TUBITAK for financially supporting me through my Ph.D. studies. The Scientific and Technological Research Council of Turkey (TUBITAK) supported this dissertation under contract EEAG-117E645 and the Student Fellowship Program BİDEB-2211.

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NOMENCLATURE

Acronyms

ANOVA	analysis of variance
disp	displayed
FOAC	fractional order admittance controller
HAM	high admittance mass
IOAC	integer order admittance controller
LAM	low admittance mass
LTI	linear time-invariant
pHRI	physical human-robot interaction

List of mathematical abbreviations

cos	cosine function
log	logarithm
max	maximum
min	minimum
sin	sine function

List of symbols

$A_{F_{\text{int}}}$	average amplitude of oscillations in interaction force
A_{F_h}	average amplitude of oscillations in force applied by human
A_P	average amplitude of oscillations in end-effector position
b_e	damping component of environment impedance
b_{eq}	damping component of equivalent impedance
b_h	damping component of human arm impedance

b_I	admittance damping of IOAC
b_F	controller parameter of FOAC (equivalent to b_I for $\alpha = 1$)
C	parasitic impedance cost
C_n	normalized parasitic impedance cost
E_{int}	energy consumed to overcome the parasitic impedance of the robot
$E_{\text{int}}^{\text{tot}}$	total energy consumption
F_h^{ave}	average force applied by human
$F_{\text{int}}^{\text{ave}}$	average interaction force
F_e	force applied by environment
F_h	force applied by human
F_{int}	sensed interaction force
$G(j\omega)$	LTI model of the robot represented in frequency domain
$G(s)$	LTI model of the robot
$H(j\omega)$	sensor dynamics represented in frequency domain
$H(s)$	sensor dynamics
j	$\sqrt{-1}$
J	convex combination of normalized objectives for multi-criteria optimization
k_e	stiffness component of environment impedance
k_{eq}	stiffness component of equivalent impedance
k_h	stiffness component of human arm impedance
$L(j\omega)$	loop transfer function in frequency domain
$L(s)$	loop transfer function in laplace domain
m_e	mass component of environment impedance
m_{eq}	mass component of equivalent impedance
m_F	controller parameter of FOAC (equivalent to m_I for $\alpha = 1$)
m_h	mass component of human arm impedance
m_I	admittance mass of IOAC
p	significance level used to test the null hypotheses

P^{ave}	average power
s	laplace domain variable
$S(j\omega)$	sensitivity of loop transfer function in frequency domain
$S(s)$	sensitivity of loop transfer function in laplace domain
$T(s)$	transfer function of the closed-loop system
$T_{\text{disp}}(s)$	transfer function of the system displayed to human
v	actual (measured) velocity of the robot
v_c	constant speed of the visual cursor
v_{des}	desired velocity
v_{ref}	reference motion trajectory for the robot
$V(s)$	actual (measured) velocity of the robot represented in laplace domain
$V_{\text{ref}}(s)$	commanded (reference) motion trajectory represented in laplace domain
w	weight
W_h	work done by human
x	position of the end-effector of the robot
$Y(j\omega)$	admittance controller represented in frequency domain
$Y(s)$	admittance controller
$Y_F(s)$	fractional order admittance controller
$Y_I(s)$	integer order admittance controller
$Z_{\text{des}}(s)$	desired impedance
$Z_{\text{disp}}(s)$	effective impedance displayed to human
$Z_e(s)$	linearized environment impedance
$Z_{\text{eq}}(s)$	equivalent impedance
$Z_h(s)$	linearized human arm impedance
Z_{FOAC}	denominator of the fractional order admittance controller
Z_{IOAC}	denominator of the integer order admittance controller
α	fractional order differintegral (i.e. fractional order integrator)
$\Delta Z(s)$	parasitic impedance function

$\Delta Z(j\omega)$	parasitic impedance function represented in frequency domain
ϕ_F	phase contribution of fractional order admittance controller
ϕ_I	phase contribution of integer order admittance controller
ρ	vector margin (i.e. robustness margin)
ρ_n	normalized vector margin (i.e. normalized robustness margin)
τ_F	m_F/b_F
τ_I	m_I/b_I
ω	frequency
ω_c	cut-off frequency
ω_n	natural frequency
ω_0	operating frequency
$\Omega_{F_{\text{int}}}$	average dominant frequency of oscillations in interaction force
Ω_{F_h}	average dominant frequency of oscillations in force applied by human

Chapter 1

INTRODUCTION

Robots are typically superior to humans at tasks that require precision, strength, and repetition, while the problem solving skills and adaptability of humans are unmatched thanks to their cognitive abilities. Physical human-robot interaction (pHRI) integrates the benefits of human and robot in tasks that involve physical interaction [Ikeura et al., 1994; Maeda et al., 2001]. From assembly or moving furniture in home/office setting [Takubo et al., 2002; Mörtl et al., 2012; Agravante et al., 2013] to industrial applications [Wojtara et al., 2009; Erden and Billard, 2016], surgery [Tavakoli et al., 2006], rehabilitation [Hogan et al., 2006; Pehlivan et al., 2016; Atashzar et al., 2017] or mission critical tasks such as manipulation in hazardous environments [Reintsema et al., 2007], collaboration of human and robot brings high performance solutions to complex problems [see the extensive reviews by Goodrich and Schultz, 2007; Santis et al., 2008; Ajoudani et al., 2018; Losey et al., 2018]. In such scenarios, the stability of the coupled system must be ensured and the controller should be robust to the changes in both human and environment dynamics for safe operation while the dyad targets to achieve a high task performance, which typically calls for robot to be transparent to the human operator. The contradicting nature of robust stability and high transparency requirements creates challenges for the researchers.

1.1 Problem Description and Related Work

The controller design for pHRI systems must pay utmost attention on the coupled stability of the human-in-the-loop system that implies the safety of the human operator by guaranteeing the safe operation of the robot; therefore, it is an indispensable aspect for any pHRI application. However, due to the complexity introduced by the presence of human operator and possible contact interactions with uncertain environments, stability characteristics of pHRI systems cannot be analyzed easily. For such analysis, one should consider that human dynamics display nonlinear, time and configuration dependent characteristics and discontinuities may occur due to the loss of contact between human operator and robot. Moreover, the interaction with an environment makes this analysis even more challenging, as the impedance of the contact environment is also likely to be nonlinear and uncertain. In such cases, for simplification, one can assume that the robot interacts with a combined impedance of human arm and environment to develop a dynamical model of the coupled system and the controller for stability analysis. Unfortunately, it is still highly challenging to develop such a model and then investigate its behaviour, which unavoidably requires cumbersome analysis.

Linear second order mass-spring-damper models have been utilized to model human arm dynamics and environment, so that the well known classical control techniques can be adopted to analyze the stability of the coupled system. This commonly used simplifying assumption allows one to investigate the basic factors affecting the coupled stability. For instance, it has been reported in the literature that the stiffness components of both the human arm and the environment models are particularly important as they have a direct effect on the coupled stability of the closed-loop system [Tsumugiwa et al., 2004; Dimeas and Aspragathos, 2016; Aydin et al., 2018]. Tsumugiwa et al. [2004] used root-locus method to determine the coupled stability of a control system designed for a pHRI task and showed that the environment stiffness is the most dominant factor contributing to the instability of the system. Duchaine and Gosselin [2008] estimated the human arm stiffness experimentally and utilized this information in a Lyapunov stability analysis to determine the critical damping value stabilizing the closed-loop system. This method relies on the maximum

arm stiffness identified offline; hence, ignores the time-varying nature of human arm dynamics. In contrast, human arm stiffness was estimated online by Gallagher et al. [2014] using EMG sensors in order to adjust the gains of an impedance controller on-the-fly based on the estimated arm stiffness to ensure stability of the coupled system. In Lamy et al. [2009], arm stiffness was estimated indirectly by measuring the grasping force applied by human. It was assumed that the tight grasp by human operator results in an increase in the stiffness reflected to robot, and the controller gains were adjusted accordingly. This method requires design of a gain scheduler and physical handles equipped with pressure sensors for the implementation.

In the absence of human and environment models, the coupled stability of pHRI systems can be also investigated using the passivity framework [Colgate and Hogan, 1988; Colgate and Schenkel, 1997]. In this approach, the human operator and the environment are assumed to act as passive elements, not injecting energy to the closed-loop system, and, hence, they do not tend to destabilize the closed-loop system. If the rest of the control system is designed to be strictly passive, then the closed-loop system is also passive, ensuring the coupled stability, provided that the system is detectable. Passivity can guarantee the stability of the closed-loop system for a broad range of human/environment models; but, unfortunately, the resulting controller performs conservatively [Colgate and Schenkel, 1997; Hulin et al., 2014], leading to a less transparent system.

Hannaford and Ryu [2002] proposed time-domain passivity approach to improve performance of haptic interfaces while preserving the passivity of the overall system. This approach utilizes a passivity observer (PO) to estimate the energy generated within the close-loop system and uses an adaptive dissipative element, called passivity controller (PC), to damp out the excessive energy in the system. This control architecture was applied to teleoperators [Ryu et al., 2004a] and its effectiveness was validated experimentally. Later, a more general version of the time-domain passivity control architecture was proposed by Ryu et al. [2004b]. Utilizing time domain passivity framework helps relax the conservativeness of the frequency domain passivity framework and promises stable human-robot interactions, even in the absence of human and environment models. However, this method

requires continual estimation of the exchanged energy between robot and human and/or environment through sensor measurements, which may prove challenging due to sampling, noise, and quantization. Furthermore, abrupt engagement of PC may disturb the quality of interaction.

Satisfying passivity throughout the interaction ensures that robot behavior is never active (i.e. energy is not generated), so that stability can be guaranteed for a large range of human/environment impedances. However, non-passive (i.e. active) systems are not necessarily unstable [Buerger et al., 2001]. This is due to the fact that passivity only considers the phase of the uncertainty, hence assumes that the magnitude of uncertainty can be arbitrarily large. However, in practice, many systems are not exposed to such large changes or uncertainties. The conservativeness of the passivity frameworks can further be relaxed by taking advantage of partial knowledge (e.g. bounds) on the models of human and/or environment. For instance, even though the dynamics of human arm changes over time, human arm impedance varies in a relatively limited range [Dolan et al., 1993; Tsuji et al., 1995]. Along these lines, Buerger and Hogan [2007] proposed a complementary stability approach to design robust controllers that can maintain robust stability for bounded ranges of human/environment impedances so that coupled stability can be ensured without the need for passivity. Similarly, Haddadi and Hashtrudi-Zaad [2010] relaxed the passivity constraints when the bounds of the environmental/human arm impedances are known.

Over the years, the researchers have searched for ways to relax the conservative constraints of robust stability, as conservative stability criteria adversely affect the performance in pHRI [Lawrence, 1993]. In particular, the tradeoff between robust stability and transparency brings a challenge in tasks that require high transparency, where human needs to feel the environment. For instance, in a robotic assisted surgery, the presence of the robot itself reflects additional impedance to the human, and hence, human may not feel the environment thoroughly, which is not desirable. The trade-off between stability and transparency [Hashtrudi-Zaad and Salcudean, 2001; Griffiths et al., 2008; Diaz et al., 2010; Willaert et al., 2014; Colonnese and Okamura, 2015] as well as the factors affecting the transparency have already been investigated in earlier studies [Hirche et al., 2005; Tavakoli

et al., 2007; Abbott and Okamura, 2007; Schauß and Peer, 2012]. As an indicator of the achievable transparency, the bounds of the dynamic range of achievable impedances, Z-width, proposed by Colgate and Brown [1994], was studied, and the methods to measure and improve the Z-width were investigated by Weir et al. [2008] and Chawda et al. [2018]. Yet, it is known that attaining perfect transparency is practically infeasible [Lawrence, 1993]. Hence, while keeping stability intact, a controller allowing for a better compromise between transparency and robust stability is always desirable for pHRI studies [Schauß and Peer, 2012].

Several control architectures have been proposed in order to improve the transparency while preserving the robust stability of the closed-loop system. Cavusoglu et al. [2002] defined a task-dependent measure to quantify a teleoperation system's ability to reflect the changes in the environment impedance, and then optimized this measure. The proposed optimization approach is similar to $\mathcal{H}_\infty$ design. Labrecque and Gosselin [2015] optimized an admittance controller by minimizing a cost function that combines metrics defined for force amplification, transparency, and task performance for bilateral interaction. Later, Labrecque and Gosselin [2018] extended this approach such that the interaction between human and robot was investigated by three different modes depending on the status of the contact between the robot and the environment. The controller was designed so that the free space movement (unilateral mode) was improved and the contact stability (bilateral mode) for the robot was ensured while the third mode allowed a smooth transition between the unilateral and bilateral modes. The experimental implementation of the proposed approach shows that an effective and versatile control of the robot is possible in the presence of human operator.

Earlier studies in pHRI rely on integer order admittance/impedance controllers to address the tradeoff between stability robustness and transparency. Alternatively, in the first part of this dissertation, we introduce fractional order admittance controllers (FOAC) for pHRI. FOAC utilizes fractional order calculus, a generalization of well-known integer order calculus, which allows the use of integrators/differentiators of arbitrary orders. Hence, the output response characteristics of the closed-loop system can be shaped by changing

the order of integration which enables more effective control on frequency-dependent response of FOAC. Therefore, adjusting this additional parameter (i.e. order of integration) of FOAC brings more flexibility while addressing the tradeoff between stability robustness and transparency.

In the second part of this dissertation, to design LTI interaction controllers (admittance and impedance controllers) for pHRI, we propose a multi-criteria optimization framework which optimizes the stability robustness and transparency. Since the dynamics of interactions between human, robot, and the environment are highly complex, it is challenging to develop an analytical framework for the same purpose, therefore a computational approach is followed in this study. Most of the earlier computational studies for optimizing the human-robot interaction have focused on the joint manipulation trajectory [Norouzzadeh et al., 2012; Losey and O'Malley, 2018], task performance [Passenberg et al., 2011; Rahman and Ikeura, 2016; Hulin, 2017], collaborative task planning and scheduling [Wilcox and Shah, 2012; Gombolay et al., 2017; Pearce et al., 2018], but not the trade-off between robust stability and transparency.

The studies closest to ours are by Buerger and Hogan [2007] and Labrecque and Goselin [2015], in which they sequentially optimized an admittance controller for stability and maximum performance. In their approach, the multi-objective optimization problem is formulated as consecutive single objective optimization problems. The drawback of such approach is that the preferences between objectives, and the order with which the single objective optimization problems are solved, are assigned a priori before having a complete knowledge on the optimization problem. Thus, solutions obtained by such sequential approaches are in general sub-optimal.

1.2 Contributions

Earlier studies focusing on the tradeoff between stability and transparency in pHRI rely on integer order interaction (admittance/impedance) controllers. In the first part of this dissertation,

- We propose fractional order admittance controllers (FOAC) for pHRI and provide evidence that such controllers can offer better robust stability characteristics while displaying higher transparency than integer order admittance controller (IOAC) [Aydin et al., 2017].
- We introduce the concept of impedance matching to enable fair comparisons between FOAC and IOAC [Aydin et al., 2018]. Specifically, by matching the impedance of FOAC to IOAC for a desired operating frequency, we show analytically that both stability robustness and transparency performance can be improved under FOAC.
- We investigate the interaction performance experimentally with 10 subjects during a task imitating a contact with a stiff environment. We extend our empirical investigations by providing results of a needle insertion experiment that involves interaction with a more complex nonlinear environment. The results provide evidence that the fractional order admittance controller is more robust than the standard admittance controller and helps to reduce the human effort in task execution.

Earlier studies including ours have already shown that a compromise between stability robustness and transparency is possible by manipulating the parameters of an interaction controller for pHRI [Buerger and Hogan, 2007; Aydin et al., 2017, 2018]. Analytical methods have proven to be prohibitive for the design of an optimal interaction controller for pHRI due to the complexity of interaction between the control parameters and the dynamics of the coupled system and also the difficulty in formulating the tradeoff between stability robustness and transparency. On the other hand, computational approaches have been quite promising [Buerger and Hogan, 2007; Labrecque and Gosselin, 2015]. Indeed,

our approach in this dissertation relies on this reasoning and proposes a controller design framework based on computational techniques. Along these lines, in the second part of this dissertation,

- We propose a multi-criteria optimization framework to design LTI interaction controllers (admittance and impedance controllers) for pHRI tasks. To our knowledge, no such general multi-criteria optimization framework has been proposed to optimize an interaction controller for a robust and transparent design.
- We propose a Pareto optimization approach which uses the concept of dominance to reach non-dominated, that is, truly optimal, set of solutions. While a sequential optimization approach makes a decision on preferences prior to optimization to solve for a single, sub-optimal solution, Pareto optimization methods allow the designer to make an informed decision by studying all possible optimal solutions that form the Pareto front. As the tradeoff among objectives can be inspected thoroughly for the interaction controller using the Pareto approach, decision making is carried out after gaining a thorough knowledge on the tradeoff.
- We show that Pareto optimization enables a fair comparison among multiple different controller structures, as the comparison can be made among the best possible performance of all controllers.
- We demonstrate such a (fair) comparison as a case study that compares FOAC and IOAC, and show that FOAC offers a better tradeoff between stability robustness and transparency than IOAC.
- We verify an optimal design and validate the comparison of FOAC with IOAC through experimental evidence collected from a pHRI study that involves contact interactions with a nonlinear environment.

1.3 Outline

The rest of this dissertation is organized as follows:

Chapter 2 presents the proposed fractional order admittance controller for pHRI. Section 2.1 presents preliminaries and the control architectures used in this study. Stability, transparency, impedance matching, and stability robustness analyses are reported in Section 2.2. Two different human subject experiments conducted to assess the task performance during interactions under FOAC and IOAC are reported in Sections 2.3 and 2.4, respectively. A thorough discussion is provided in Section 2.5.

The multi-criteria optimization framework proposed in this dissertation and its application are presented in Chapter 3. Section 3.1 introduces the computational multi-criteria interaction controller design framework. Section 3.2 presents the running examples for which the interaction control architectures, and transparency and stability robustness metrics are introduced. The objective functions are defined in Section 3.3. Pareto optimization is presented in Section 3.4. Human subject experiments conducted to assess the transparency during interactions under optimal FOAC and IOAC are reported in Section 3.5.

Conclusions and future research directions are provided in Chapter 4.

Chapter 2

FRACTIONAL ORDER ADMITTANCE CONTROL FOR PHYSICAL HUMAN-ROBOT INTERACTION

In this chapter, we introduce fractional order admittance controller (FOAC) for pHRI. This control scheme relies on the fractional order calculus, which allows the use of integrators/differentiators of arbitrary orders. Hence, in addition to adjusting the usual admittance controller parameters (i.e. admittance mass and damping), one can also change the output response characteristics of the closed-loop system by changing the order of integration. In particular, order of integration enables more effective control of frequency-dependent response of FOAC and brings more flexibility to adjust the trade-off between stability and transparency, making it well-suited for applications that involve pHRI. In this chapter, the stability and robustness of such a controller and its effect on human effort and task performance during contact interactions with linear and nonlinear environments are investigated and compared to those of an integer order admittance controller (IOAC).

2.1 Preliminaries

2.1.1 Fractional Order Control

Fractional order calculus, a generalization of well-known integer order calculus, allows differentiation and integration of arbitrary orders. Fractional order calculus has been successfully utilized in many application areas, ranging from modeling of viscoelastic materials [Ayyildiz et al., 2014] to motion control of robotic systems. Impedance controllers based on fractional order calculus have been proposed and analyzed in [Tokatli and Patoglu, 2015, 2018] for haptic rendering.

Calculating a fractional order derivative/integral (differintegral) is not trivial. There exist multiple mathematically well-founded definitions for differintegration and one has to choose the appropriate definition based on the application area. In this study, the Grunwald-Letnikov definition is used for calculation of fractional order differintegrals, since this definition enables easier implementation in discrete time domain [Chen et al., 2009].

The Grunwald-Letnikov definition for fractional order differintegral is given as

$$D^\alpha y(t) = \lim_{h \rightarrow 0} \frac{1}{h^\alpha} \sum_{i=0}^{(t-a)/h} {}^\alpha C_i y(t - ih) \quad (2.1)$$

where α is the order of the differintegral, h is the step size of the calculation, a is the window length, and ${}^\alpha C_i$ can be evaluated recursively from

$${}^\alpha C_0 = 1, \quad {}^\alpha C_i = {}^\alpha C_{i-1} \left(1 - \frac{\alpha + 1}{i}\right), \quad i = 1, 2, \dots \quad (2.2)$$

Fractional order differintegral is a linear operator; hence, fractional order systems and controllers can be designed as linear time-invariant (LTI) systems and analyzed using familiar methods. However, fractional order differintegral is a non-local operator, that is, it has a memory and relies on the whole history. In real-time implementation, relying upon the short memory principle, the summation is approximated using a finite horizon into the recent past, as the earlier values are known to have a rapidly decaying influence on the current solution.

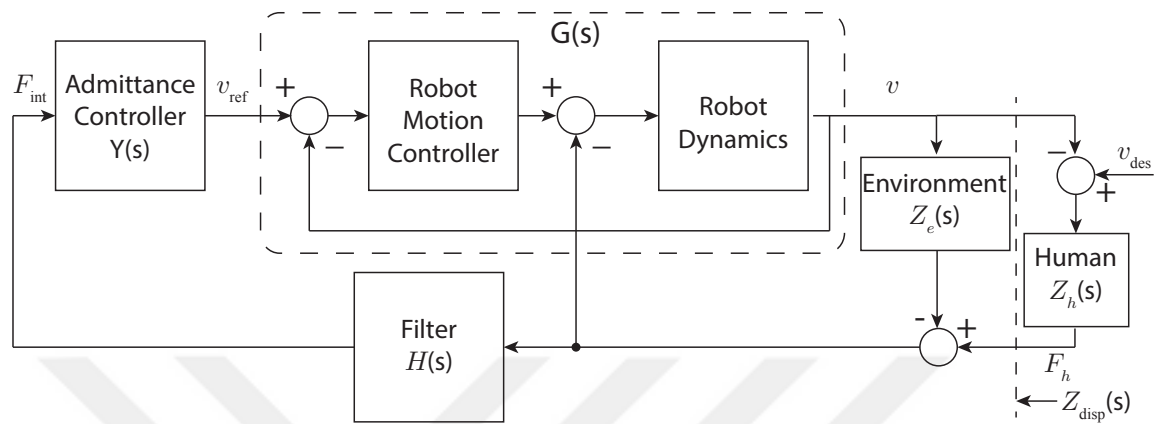


Figure 2.1: Control architecture of the pHRI system

2.1.2 Control Architecture

Figure 2.1 shows an admittance control architecture of the pHRI system where the human, robot, and environment are physically interacting with each other. Human operator is assumed to grasp the end-effector of the robot to move it with a desired velocity, v_{des} , which is determined mostly by the task or, in some cases, by the human operator. To achieve this velocity, she/he exerts a force, F_h , to the end-effector of the robot and interacts with the environment through the robot. In our system, the resultant force due to the interaction of the human, robot, and the environment is sensed by a force sensor with some dynamics, $H(s)$, and, the sensed interaction force, F_{int} , is sent to the admittance controller of the robot, $Y(s)$, so that a reference velocity profile, v_{ref} , is generated. Then, robot's motion controller transmits sufficient torque to its joints in order to closely achieve the reference velocity, v_{ref} . It is assumed that the internal motion controller of the robot that follows the given velocity profile is fast enough to compensate for any disturbances coming from the environment. The transfer function of the closed loop system is given by

$$T(s) = \frac{V(s)}{F_{\text{int}}(s)} = \frac{G(s)Y(s)}{1 + G(s)Y(s)H(s)Z_{\text{eq}}(s)} \quad (2.3)$$

where $G(s)$ is the LTI model of the robot, and $V(s)$ is its measured (actual) end-effector velocity. Human and environment are assumed to be coupled, and the equivalent impedance is

represented as $Z_{eq} = Z_h + Z_e$, where Z_h and Z_e represent linearized human and environment impedances, respectively.

Using the control architecture given in Figure 2.1, we compare IOAC and FOAC in terms of stability and closed loop impedance characteristics.

2.1.2.1 Integer order admittance controller

IOAC has been already used in earlier pHRI studies in the following form:

$$Y(s) = \frac{1}{Z_{IOAC}} = \frac{1}{m_I s + b_I} \quad (2.4)$$

where $Z_{IOAC}(s)$ represents the denominator of the IOAC, and m_I and b_I are the admittance controller parameters, corresponding to mass and damping, respectively.

2.1.2.2 Fractional order admittance controller

FOAC is defined as

$$Y(s) = \frac{1}{Z_{FOAC}(s)} = \frac{1}{m_F s^\alpha + b_F} \quad (2.5)$$

where α corresponds to the fractional order of the integrator. Here, $Z_{FOAC}(s)$ stands for the denominator of the FOAC, and m_F and b_F are the admittance controller parameters. In this dissertation, the range of the integration order is kept as $0 < \alpha \leq 1$. Thanks to the analytical nature of fractional order differintegration, as the integration order is decreased gradually from 1 to 0, the inertial energy storage characteristics of the controller decay and energy dissipation characteristics dominate. For $\alpha = 0$, the controller acts like a pure damper. On the other hand, when the integration order is $\alpha = 1$, FOAC becomes IOAC. Therefore, the effective mass and damping [Tokatli and Patoglu, 2018] supplied by the controller to the system change depending on the integration order α , while dissipative effects are present throughout the range $0 < \alpha < 1$. To demonstrate the effect of integration order on dynamical response of FOAC, consider Z_{FOAC} expressed in the frequency domain

$$\begin{aligned} Z_{FOAC}(j\omega) &= m_F (j\omega)^\alpha + b_F \\ &= b_F + m_F \omega^\alpha \cos\left(\frac{\alpha\pi}{2}\right) + jm_F \omega^\alpha \sin\left(\frac{\alpha\pi}{2}\right) \end{aligned} \quad (2.6)$$

In this equation, the effective mass and damping provided by FOAC are $m_F \omega^{\alpha-1} \sin(\frac{\alpha\pi}{2})$ and $b_F + m_F \omega^\alpha \cos(\frac{\alpha\pi}{2})$, respectively, whereas these values are simply m_I and b_I for IOAC. Hence, unlike in the integer order case, the effective damping in FOAC is frequency-dependent, and can be adjusted by altering the integration order α . This property of FOAC is of interest for pHRI tasks, as it can improve stability robustness of interactions in tasks involving contacts with environment.

2.1.3 LTI Models of Robot, Sensor, Human Arm, and Environment

2.1.3.1 Robot Model:

In our experiments, subjects interact with a UR5 robot (Universal Robots Inc.) to perform pHRI tasks. Since the dynamical model of the robot is not provided by the manufacturer, it is obtained experimentally along the horizontal axis for a specific joint configuration. That is, a transfer function $G(s)$ of the robot is estimated between recorded $V(s)$ and commanded (reference) $V_{\text{ref}}(s)$ velocities of the end-effector, where

$$G(s) = \frac{1.45\text{E}-6s^3 - 0.75s^2 + 3.92\text{E}5s + 5.48\text{E}7}{s^4 + 190.9s^3 + 2.73\text{E}4s^2 + 1.72\text{E}6s + 5.55\text{E}7} \quad (2.7)$$

2.1.3.2 Sensor Dynamics:

In this study, the force sensing mechanism is assumed to have the following dynamics including time-delays and filtering:

$$H(s) = \frac{0.01336s^2 + 3.716s + 997.4}{s^2 + 44.42s + 997.4} \quad (2.8)$$

2.1.3.3 Human Arm and Environment Impedance:

For the computational analyses of stability and transparency, human arm impedance is modeled as a second order LTI system as

$$Z_h(s) = \frac{m_h s^2 + b_h s + k_h}{s} \quad (2.9)$$

where m_h, b_h, k_h represent human arm mass, damping, and stiffness, respectively. This model is sufficient for capturing the general trends of the human arm dynamics, while keeping the complexity of the equations at a tractable level. Furthermore, such linear model for human arm dynamics was validated for time periods shorter than the time needed for humans to actively change their arm parameters [Hogan, 1989], and it was also shown that the parameters appear not to change for periods up to 1.2 s.

The contact environment can be modeled with a similar linearised model as

$$Z_e(s) = \frac{m_e s^2 + b_e s + k_e}{s} \quad (2.10)$$

where m_e, b_e, k_e represent mass, damping, and stiffness components of environment model in general, respectively. In our analyses, we combine human arm and environment impedance, and investigate the stability robustness to variations in the components of the equivalent impedance. The equivalent impedance used in our study is $Z_{eq}(s) = \frac{m_{eq}s^2 + b_{eq}s + k_{eq}}{s}$, where equivalent stiffness, damping, and mass become $k_{eq} = k_h + k_e$, $b_{eq} = b_h + b_e$, and $m_{eq} = m_h + m_e$, respectively.

2.2 Analyses of the Controllers

This section investigates the coupled stability of the proposed FOAC and compares it with IOAC. Furthermore, the transparency of these systems are also investigated using the effective impedance analysis [Mehling et al., 2005; Colonnese et al., 2015].

In these analyses, contact environment is modelled as a spring with stiffness of k_e , where environment impedance is $Z_e = k_e/s$. In our analyses, we investigate the stability robustness to variations in the stiffness component of the equivalent impedance, which is the main factor affecting the stability as suggested in earlier studies [Tsumugiwa et al., 2004; Dimeas and Aspragathos, 2016].

2.2.1 Stability

For safe pHRI applications, it is imperative to guarantee the coupled stability of the closed-loop system. Stability analysis of interaction control is challenging, as the standard tools used for servo control cannot be applied. In particular, as noted by Buerger and Hogan [2007], two fundamental differences exist for interaction control systems: the closed-loop stability and performance cannot be predicted and characterized using the open-loop transfer function, and the controller does not predictably affect the stability and performance of the coupled system. Consequently, there exists no obvious way to analytically study stability and performance of such systems, while computational approaches have been shown to provide promising results [Buerger and Hogan, 2007].

Along these lines, we compare performance of FOAC with IOAC through computational stability and transparency analyses of these controllers. It is important to note that fractional order nature of the control systems makes any form of analytical analysis even more challenging.

The stability characteristics of the coupled system is analyzed for different controller parameters using stability maps. A stability map is a graphical representation of the controller parameters for which the resulting closed-loop system becomes stable for a range of environment/human arm impedances. The stability analysis is performed by numerically studying the location of the closed-loop poles of the system. The search for a stable set

of controller parameters is relatively straightforward when the admittance controller is of integer order. However, when a fractional order element is used in the control loop, the resulting characteristic equation no longer takes a polynomial form; hence, the stability analysis becomes more involved.

For fractional order systems that are of commensurate order, checking the stability of the system with a non-polynomial characteristic equation can be accomplished by performing a transformation from the fractional order domain to the integer order domain. According to Matignon's theorem [Matignon, 1998; Chen et al., 2009], the resulting integer order system possesses equivalent stability characteristics as the fractional order system.

The stability maps for FOAC ($\alpha = 0.4$ and 0.7), and IOAC ($\alpha = 1$) are constructed to investigate the effect of integration order α on stability robustness to the changes in equivalent stiffness k_{eq} of the system. The range for the values of k_{eq} is set to be comparable to the maximum value of human arm stiffness reported in Dolan et al. [1993] and Tsuji et al. [1995]. In these analyses, it is assumed that human always maintains his/her contact with the end-effector of the robot. In such a condition, mass and damping levels in human arm model would not change significantly, where the arm stiffness may change due to the co-contraction of muscles. Hence, the robustness of the proposed controller is investigated for changes in equivalent stiffness, as it has been reported that change in stiffness of human arm and/or environment significantly contributes to the instabilities observed in pHRI [Tsumugiwa et al., 2004; Dimeas and Aspragathos, 2016]. In particular, the stability analyses are conducted for a range of equivalent stiffness values, while typical values of $b_h = 15$ Ns/m and $m_h = 1.5$ kg are used for the reflected arm damping and mass, respectively.

Figure 2.2a depicts the stability map for IOAC for $k_{eq} \in \{410 - 810 \text{ N/m}\}$, where a relatively large range of values are utilized for equivalent stiffness since the stiffness of human arm is assumed to be coupled with that of the environment. From these plots, the destabilizing nature of the equivalent stiffness can be observed; as the equivalent stiffness increases, the area for which the closed-loop system is stable gets smaller. Moreover, it can be seen that higher admittance damping is required to stabilize the system for higher values

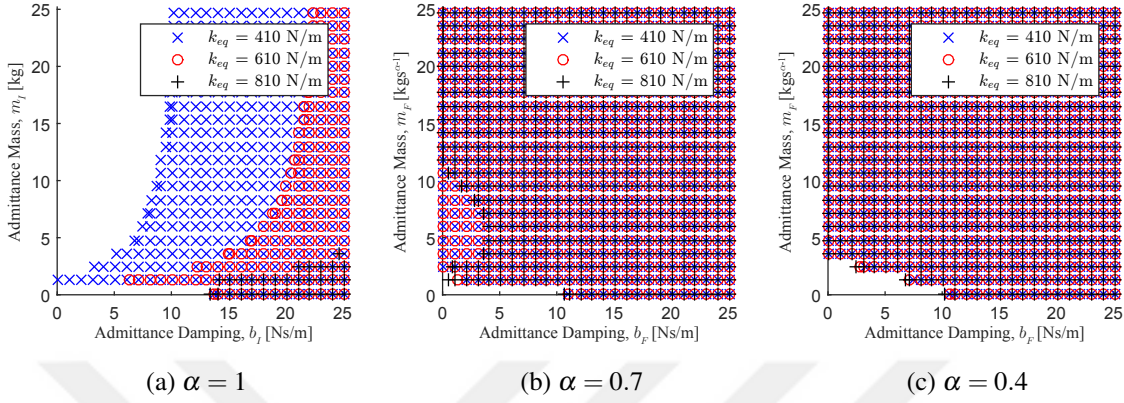


Figure 2.2: Stability maps of pHRI system for stiffness range $k_{eq} \in \{410 - 810\}$ N/m under (a) IOAC $\alpha = 1$, (b) FOAC $\alpha = 0.7$, and (c) FOAC $\alpha = 0.4$.

of equivalent stiffness, which is consistent with the findings reported in Tsumugiwa et al. [2004] and Dimeas and Aspragathos [2016].

Similar analysis is conducted for FOAC and the resulting stability maps for $\alpha = 0.7$ and $\alpha = 0.4$ are presented in Figures 2.2b and 2.2c, respectively. It can be observed from these plots that the change in the stability regions of FOAC for varying equivalent stiffness levels is much less compared to that of IOAC. In addition, it can be observed that robustness to variations in equivalent stiffness increases as integration order α decreases (Figures 2.2b and 2.2c).

These results indicate that, under the assumptions of a second order LTI model for human arm and contact interaction with a relatively stiff environment modeled as a linear spring, parameters of FOAC can exhibit significantly higher levels of robustness to the changes in the environment/human arm stiffness values.

2.2.2 Transparency

We computationally compare the transparency of pHRI systems under IOAC and FOAC through studying their effective closed loop impedances. For the system in Figure 2.1, the closed loop impedance displayed to human $Z_{disp}(s)$ is

$$Z_{disp}(s) = \frac{F_h(s)}{V(s)} = \frac{1 + G(s)Y(s)H(s)Z_e(s)}{G(s)Y(s)H(s)} \quad (2.11)$$

The impedance reflected to human can then be decomposed into effective mass ($EM(\omega) = \omega^{-1} \Im^+ \{Z_{\text{disp}}(j\omega)\}$), effective damping ($ED(\omega) = \Re^+ \{Z_{\text{disp}}(j\omega)\}$), and effective stiffness ($ES(\omega) = \omega \Im^- \{Z_{\text{disp}}(j\omega)\}$) components, as suggested in Mehling et al. [2005] and Colonese et al. [2015], where $Z_{\text{disp}}(j\omega)$ is the frequency response of the closed loop impedance transfer function.

For a comparison of IOAC with FOAC, a stiffness value of $k_e = 610$ N/m is selected for the environment. The admittance controller parameters are set as $m_F = \{5, 20\}$ kgs $^{\alpha-1}$, $m_I = \{5, 20\}$ kg, and $b_F = b_I = 25$ Ns/m. These values are chosen from the stable region in the stability maps in Figure 2.2. The effective mass, damping, and stiffness for these systems as functions of frequency are depicted in Figures 2.3a, 2.3b, and 2.3c, respectively. It can be observed from these plots that the effective mass stays close to zero up to the natural frequency (ω_n), since effective stiffness dominates the dynamical behavior within that range. When $\omega > \omega_n$, the effective mass for IOAC is higher than that of FOAC. The effective stiffness is higher under FOAC than that of IOAC for $\omega < \omega_n$. Afterwards, it becomes close to zero as the effective mass dominates the behavior of the system for $\omega > \omega_n$. Natural frequency of the system under FOAC is higher than that of IOAC, since higher effective stiffness and lower effective mass are rendered under FOAC. This behaviour can also be observed by inspecting the magnitude and phase plots (Figures 2.3d and 2.3e) of the closed loop system.

Effective damping analysis in Figure 2.3c reveals that the effective damping supplied by FOAC remains high for a larger range of frequencies compared to IOAC and displays an increase with frequency almost up to the natural frequency of the system. This behaviour is beneficial as higher effective damping at higher frequencies contributes to stability robustness, while relatively lower effective damping at lower frequencies may lead to higher task performance due to better transparency.

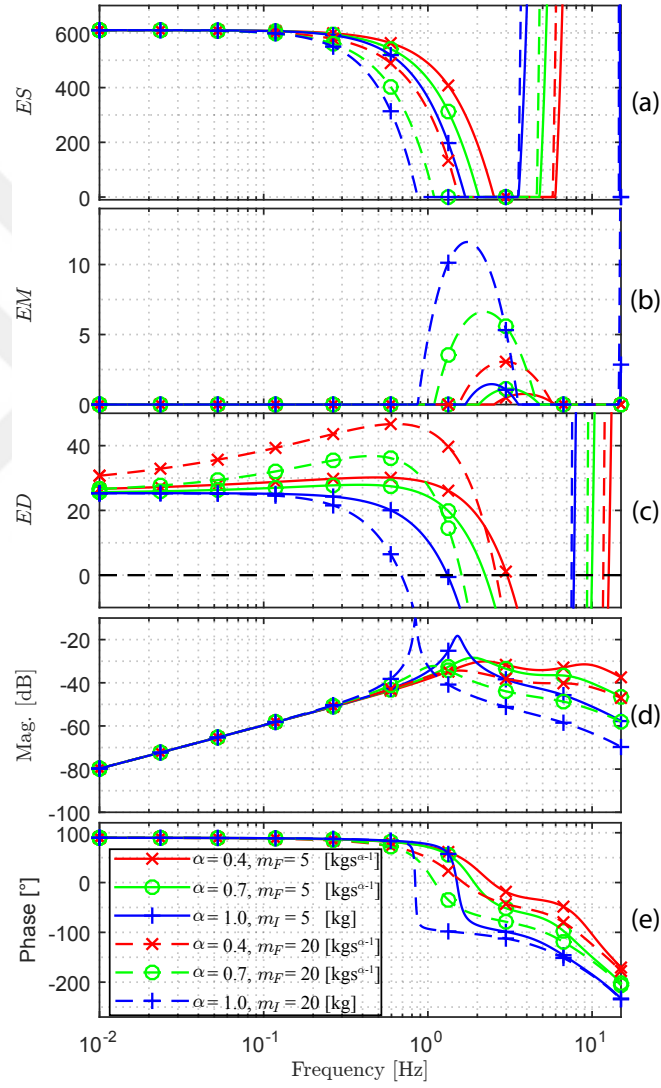


Figure 2.3: Effective stiffness (a), effective mass (b), and effective damping (c) of the impedance transfer function. Magnitude (d) and phase (e) plots of the closed loop transfer function.

2.2.3 Impedance Matching

Providing the range of controller parameters under which the closed loop system stays stable, stability maps are useful to study the stability robustness of a system under uncertainties. However, stability maps cannot be employed to directly compare controllers of different integration orders, as the control parameters for each integration order have different physical characteristics and different units. Furthermore, given the frequency dependent nature of FOAC, a direct analytical mapping between IOAC and FOAC parameters can only be provided at a particular frequency.

To enable a comparison between IOAC and FOAC parameters, we propose impedance matching to map the parameters of FOAC to the parameters of an equivalent IOAC at a given frequency of interest. In particular, given a frequency (ω_0), the closed loop impedance under FOAC can be matched to that of IOAC using Equation (2.11). Since Z_e , H , and G are the same for both controllers in Equation (2.11), equating the controller admittance transfer functions Y becomes sufficient for the closed loop impedance matching at a particular frequency ω_0 as follows

$$Y_I(j\omega_0) = Y_F(j\omega_0) \implies \frac{1}{m_I j\omega_0 + b_I} = \frac{1}{m_F (j\omega_0)^\alpha + b_F} \quad (2.12)$$

It can be shown that the above complex equality is satisfied, when the following equivalence relations hold among the controller parameters

$$b_I = b_F + m_F \omega_0^\alpha \cos\left(\frac{\pi\alpha}{2}\right) \quad (2.13)$$

$$m_I = m_F \omega_0^{\alpha-1} \sin\left(\frac{\pi\alpha}{2}\right) \quad (2.14)$$

Under the impedance matching, these equations provide a direct mapping among parameters of FOAC and IOAC, at ω_0 . Note that, while FOAC is designed as a linear time-invariant (LTI) system and analyzed using familiar methods, FOAC provides frequency dependent admittance controller parameters. One can observe from these equations that, for $\alpha < 1$, the mapped damping parameter of FOAC increases, and the mapped mass parameter of FOAC decreases, as ω_0 increases. However, the controller parameters for an IOAC are independent of ω . Frequency dependence of FOAC is beneficial as low values of

mapped damping parameter at low frequencies can improve transparency, while high values of mapped damping parameter at high frequencies is beneficial for stability robustness. Similarly, decrease in mapped mass parameter as frequency increases may provide improved transparency. These effects are consistent with the observations due to the effective impedance analysis of the closed loop system in the previous subsection.

2.2.4 Stability Robustness

The phase lag added by a controller can be studied as an indicator of the stability robustness for LTI systems. Let $\tau_F = m_F/b_F$ and $\tau_I = m_I/b_I$ be defined as the time constants for FOAC and IOAC, respectively. The phase contributions of IOAC and FOAC under impedance matching at a given frequency ω_0 can be derived as

$$\phi_I = -\tan^{-1}(\tau_I \omega) = -\tan^{-1} \left(\frac{\tau_F \omega_0^{\alpha-1} \sin(\frac{\pi\alpha}{2})}{1 + \tau_F \omega_0^\alpha \cos(\frac{\pi\alpha}{2})} \omega \right) \quad (2.15)$$

$$\phi_F = -\tan^{-1} \left(\frac{\tau_F \omega^\alpha \sin(\frac{\pi\alpha}{2})}{1 + \tau_F \omega^\alpha \cos(\frac{\pi\alpha}{2})} \right) \quad (2.16)$$

Studying the case when $\alpha < 1$, as $\omega \rightarrow 0$, ϕ_I and ϕ_F both go to zero, whereas as $\omega \rightarrow \infty$, $\phi_I \rightarrow \pi/2$, while $\phi_F \rightarrow \pi\alpha/2$. The values of ϕ_I and ϕ_F are close to each other for $\omega \leq \omega_0$. On the other hand, ϕ_I increases rapidly as a function of ω especially for $\omega > \omega_0$, whereas ϕ_F increases with a slower rate. Thus, for frequencies, especially beyond ω_0 , IOAC always adds more phase to the loop transfer function than FOAC does, which means that the phase lag under FOAC is lower.

In general, the phase margin alone is not a sufficient indicator of the stability robustness of a system, while the vector margin, defined as the inverse of the maximum magnitude of loop sensitivity function $S(s)$ [Åström and Murray, 2010], can be studied for more conclusive results. The sensitivity function $S(s)$ for the system can be defined as

$$S(s) = \frac{1}{1+L(s)} = \frac{1}{1+G(s)Y(s)H(s)Z_{eq}(s)} \quad (2.17)$$

where $L(s)$ denotes the loop transfer function. From this equation, one can note that a larger loop gain reduces the magnitude of the sensitivity function and leads to a more robust

system. For a given GHZ_{eq} , one can compare the controller gains of IOAC and FOAC to investigate which one is more robust under impedance matching at ω_0 . In the equations below, Z_{FOAC} and Z_{IOAC} stand for the denominator of FOAC and IOAC, respectively.

$$\begin{aligned}
 |Z_{FOAC}|^2 &= m_F^2 \omega^{2\alpha} + b_F^2 + 2m_F b_F \cos\left(\frac{\pi\alpha}{2}\right) \omega^\alpha \\
 |Z_{IOAC}|^2 &= m_I^2 \omega^2 + b_I^2 \\
 &= m_F^2 \omega_0^{2\alpha-2} \sin^2\left(\frac{\pi\alpha}{2}\right) \omega^2 + b_F^2 \\
 &\quad + m_F^2 \omega_0^{2\alpha} \cos^2\left(\frac{\pi\alpha}{2}\right) + 2m_F b_F \omega_0^\alpha \cos\left(\frac{\pi\alpha}{2}\right)
 \end{aligned}$$

As $\omega \rightarrow 0$, $|Z_{FOAC}|^2 \rightarrow b_F^2$, whereas $|Z_{IOAC}|^2 \rightarrow b_F^2 + m_F^2 \omega_0^{2\alpha} \cos^2(\pi\alpha/2) + 2m_F b_F \omega_0^\alpha \cos(\pi\alpha/2)$. As $\omega \rightarrow \infty$, $|Z_{IOAC}|^2$ increases with ω^2 while $|Z_{FOAC}|^2$ increases with $\omega^{2\alpha}$, which has a slower rate when the differentiation order $\alpha < 1$.

Consequently, given that the magnitude of the sensitivity function is lower under FOAC, the vector margin of FOAC is larger than that of an IOAC with a matched impedance at a given frequency ω_0 . These results are consistent with the stability map analysis presented in Section 2.2.1.

2.3 A Controlled pHRI Experiment: Continuous Contact with a Spring

In pHRI, maximizing task performance, while maintaining stability is desired. The effective impedance analysis shows that high effective damping under FOAC can be sustained for a larger range of frequencies, which is desirable for stable interactions. This feature of FOAC can improve human performance in pHRI tasks involving especially contact interactions with environment.

A controlled human subject experiment was designed to further investigate this frequency-dependent damping feature of FOAC, and effect of controller type (i.e. FOAC vs IOAC) and admittance parameters m_F and m_I on performance in a pHRI task. The task involved contact interactions with a linear spring, where spring represented a relatively stiff environment.

2.3.1 Experimental Procedure

In our experimental setup, a spring ($k_e = 610$ N/m) is connected between a fixed support and the end-effector of UR5 robot, as shown in Figure 2.4a. The subject grasps the handle between the spring and the robot to guide the end-effector and compress the spring. The spring simply represents the environment in which the robot guided by a human operator is in continuous contact, as in drilling a wall or inserting a needle into soft tissue. In the experiments, the subjects are asked to compress the spring up to a certain position (ramp phase, Figure 2.4b), and then, hold it at that position for 10 seconds (hold phase, Figure 2.4c). For visual feedback to the subjects, a virtual object (black rectangle, labeled as "O" in Figure 2.4b) having a finite size is displayed on the computer screen and its movement is virtually linked to that of the end-effector guided by the subject. The motion of the end-effector is constrained to stay on a straight path, and the admittance controller scheme described in Section 2.1.2 is utilized. In order to make the compression rate of the spring equal for each subject, a visual cursor (i.e. blue rectangle, labeled as "C") moving with a constant speed ($v_c = 0.5$ cm/s) is also displayed on the computer screen. The cursor stops when it reaches the end of the ramp phase, labeled as "hold position". Following, the subject is required to hold the spring at this position for 10 seconds (hold phase) to

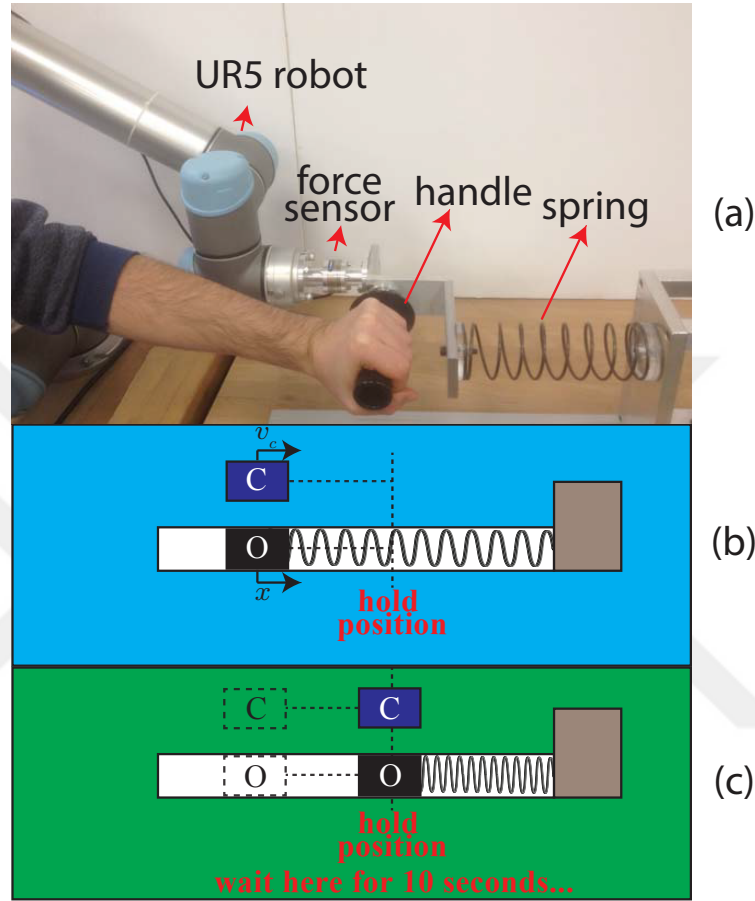


Figure 2.4: The experimental setup and visual feedback provided to the subjects during the experiments.

complete the task (Figure 2.4c). The details of the experimental procedure is available in our earlier publication [Aydin et al., 2017].

We compared subjects' performance under IOAC ($\alpha = 1$) and FOAC ($\alpha = 0.7$). Since parameters m_F and m_I are the coefficients in front of the integrator in admittance controller, we also investigated their effect on performance for low (i.e. LAM, $m_F = 5 \text{ kgs}^{\alpha-1}$, $m_I = 5 \text{ kg}$) and high (i.e. HAM, $m_F = 20 \text{ kgs}^{\alpha-1}$, $m_I = 20 \text{ kg}$) values. On the other hand, the admittance damping ($b_F = b_I = 25 \text{ Ns/m}$) was kept constant throughout the experiment, since it does not have a direct relation with the integrator. These values were chosen by considering the stable regions of the stability maps given in Figure 2.2. Hence, four different conditions (FOAC-LAM, IOAC-LAM, FOAC-HAM, IOAC-HAM) were tested in this

experiment. Each condition was repeated 9 times. Thus, there were 36 (4×9) trials in the experiment, which were displayed to the subjects in random order, while the order was same for each subject. Prior to the actual experiment, each subject was given a training session to get her/him familiar with the setup. 10 subjects (5 males and 5 females, average age = 28 ± 5) participated in this experiment. The subjects gave informed consent about their participation in the experiment. The experimental study was approved by the Ethical Committee for Human Participants of Koc University.

2.3.2 Data Collection and Metrics

During the experiment, the robot constrains the motion of the subjects along a horizontal line while they compress the spring. The force F_h applied by a subject is the sum of the force F_e required for compressing the spring and generating the motion trajectory of the robot (i.e. interaction force F_{int}) $F_h = F_e + F_{\text{int}}$, where $F_e = k_e \Delta x$ (Δx is the amount of compression) is not influenced by the controller type or admittance parameters m_F and m_I . F_{int} is the interaction force measured by a force sensor (Mini40, ATI Inc.), filtered, and fed back to the admittance controller. The force applied by the subject F_h and the interaction force F_{int} are linearly dependent on each other, since F_e depends on only the amount of compression, and is independent of viscous and inertial effects coming from the controller and the robot. Hence, by inspecting the interaction force alone, we can deduce how the force applied by the subject is influenced by the changes in admittance controller, and parameters m_F and m_I .

All the metrics evaluated in this section are based on this F_{int} (the filtered value of the interaction force), unless otherwise is specified. We use average power ($P^{\text{ave}} = 1/(t_f - t_i) \int_{t_i}^{t_f} |F_{\text{int}}(t) \cdot v(t)| dt$), and average interaction force ($F_{\text{int}}^{\text{ave}} = 1/(t_f - t_i) \int_{t_i}^{t_f} |F_{\text{int}}(t)| dt$) to quantify the interaction performance under different task conditions, where, t_i and t_f are the beginning and ending times of a phase (ramp or hold), respectively. We also inspect average dominant frequency of oscillations in interaction force ($\Omega_{F_{\text{int}}} = 1/N \sum_{i=1}^N 1/(2|t_{\text{max},i} - t_{\text{min},i}|)$), where $t_{\text{max},i}$ ($t_{\text{min},i}$) represents the time at i^{th} local maximum (minimum), and N stands for the total number of consecutive local minima and

maxima in interaction force F_{int} . The results are also verified by FFT analysis in the frequency domain. In addition, average amplitude of oscillations in interaction force ($A_{F_{\text{int}}} = 1/N \sum_{i=1}^N |F_{\text{max},i} - F_{\text{min},i}|$) and end-effector position ($A_P = 1/N \sum_{i=1}^N |x_{\text{max},i} - x_{\text{min},i}|$) are computed, where $F_{\text{max},i}$ ($F_{\text{min},i}$) represents the i^{th} local maximum (minimum) in interaction force F_{int} , and $x_{\text{max},i}$ ($x_{\text{min},i}$) indicates i^{th} local maximum (minimum) in end-effector position x .

2.3.3 Data Analysis

For each subject, the performance metrics were calculated for the both phases (except A_P , which was evaluated for the hold phase only) of all trials and then normalized for the analysis (Figure 2.5). We initially performed two-way ANOVA to investigate the statistical significance of these results. We observed that the factors (admittance parameters m_F and m_I , and type of controller) had significant effects on the performance and there was an interaction between them. Further analysis was performed to evaluate the individual effects of parameters m_F and m_I , and controller type on interaction performance. In all statistical analyses, a significance level of $p = 0.005$ was used to test the null hypothesis.

2.3.4 Results

Figure 2.5a demonstrates average power P^{ave} during both phases. P^{ave} was significantly lower under FOAC than that of IOAC during both phases when LAM was used. P^{ave} was significantly lower under FOAC than that of IOAC during only the ramp phase when HAM was used. The change in admittance parameter m_F did not affect P^{ave} significantly under FOAC.

Figure 2.5b illustrates average interaction force $F_{\text{int}}^{\text{ave}}$ during both phases. We observed a statistically significant effect of controller type on $F_{\text{int}}^{\text{ave}}$. Specifically, $F_{\text{int}}^{\text{ave}}$ was significantly lower under FOAC than that of IOAC during both phases. The effect of change in admittance parameter m_F on $F_{\text{int}}^{\text{ave}}$ was not significant under FOAC.

Figure 2.5c shows average amplitude of oscillations in interaction force $A_{F_{\text{int}}}$ during both phases. $A_{F_{\text{int}}}$ was significantly lower under FOAC than that of IOAC during both phases.

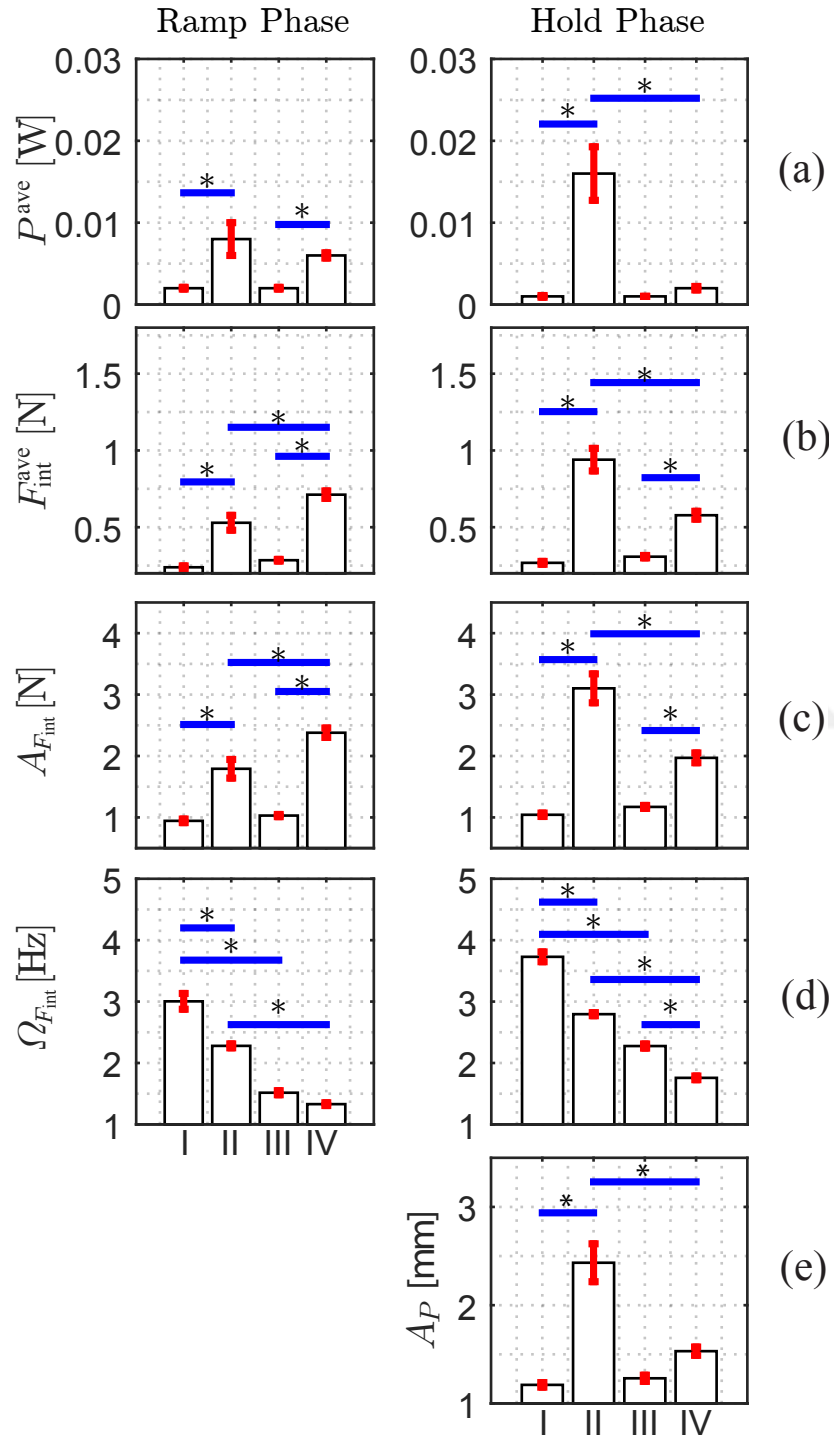


Figure 2.5: The means and the standard errors of means of normalized performance metrics (I: FOAC-LAM, II: IOAC-LAM, III: FOAC-HAM, IV: IOAC-HAM. Horizontal bars with * on top indicate statistical significance between results of the two corresponding conditions).

The change in admittance parameter m_F did not affect $A_{F_{\text{int}}}$ significantly under FOAC.

Average dominant frequency of oscillations in interaction force $\Omega_{F_{\text{int}}}$ is illustrated in Figure 2.5d. $\Omega_{F_{\text{int}}}$ was significantly higher under FOAC than that of IOAC during both phases when LAM was used. $\Omega_{F_{\text{int}}}$ was significantly higher under FOAC than that of IOAC during the hold phase for HAM.

Average amplitude of oscillations in end-effector position A_P during the hold phase is shown in Figure 2.5e. A_P was significantly lower under FOAC than that of IOAC when LAM was used. The effect of change in admittance parameter m_F on A_P was not significant under FOAC.

2.3.5 Discussion of the Experimental Results

We investigated the effect of FOAC on human performance in a pHRI task involving contact interactions with a relatively stiff environment; compressing a spring with a certain rate (ramp phase) and holding it there for 10 seconds (hold phase). Due to the frequency-dependent nature of damping in FOAC, the oscillations in the interaction force were better absorbed in both phases of the task (Figure 2.5c).

For FOAC, the higher admittance parameter m_F did not result in significant increase in $F_{\text{int}}^{\text{ave}}$, P^{ave} and $A_{F_{\text{int}}}$, while higher m_F resulted in significantly lower average frequency $\Omega_{F_{\text{int}}}$ for force oscillations. These results indicate that frequency dependent behavior of effective damping in the fractional order case is the main factor in achieving the desired level of dissipation for the task at hand. The main effect of higher m_F and m_I is to increase the effective mass of the system, and to decrease the system natural frequency.

As a downside of FOAC, frequency of oscillations in force increased slightly (Figure 2.5d) due to lower effective mass rendered by FOAC (Figure 2.3b). This increase may not be desirable during contact interactions. However, amplitudes of oscillations in force and end-effector position were significantly lower than those of IOAC, since FOAC supplied more effective damping to the system (Figures 2.5c, and 2.5e). Moreover, average power, average interaction force, and average amplitude of oscillations in interaction force were all significantly lower under FOAC (Figures 2.5a, 2.5b, and 2.5c).

2.4 Needle Insertion Experiment

The results of the experiment reported in Section 2.3.4 shows that FOAC can improve performance in tasks involving contact interactions. In that controlled experiment, the task involved an interaction with a linear spring, which is sufficient for exploring the potential advantages of FOAC over IOAC. Here, task performance under FOAC and IOAC is further compared in a more complicated pHRI scenario where contact interactions with a nonlinear, viscoelastic, and layered environment are investigated. Needle insertion experiments were performed with soft silicon samples and task performances under FOAC and IOAC were compared using the metrics defined in Section 2.3.2.

Needle insertion is commonly used in many medical procedures including biopsies, brachytherapy, injection therapy, and epidural anesthesia. The insertion of a needle into soft tissue involves distinct phases [Gokgol et al., 2012]. The process starts with the deformation of the soft tissue under the force exerted by the needle. This deformation continues until rupture occurs, the stage of pure deformation ends, a quick drop in force is observed, and a mixed stage of penetration and deformation starts. At this stage, as the needle continues its movement through the soft tissue, the forces tend to increase until the needle reaches to another layer or comes to a full stop. During the procedure, the operator advances the needle into tissue by appreciating the magnitude of these interaction forces.

In our scenario, the human operator advances the needle into two silicon samples, placed back to back to imitate a layered soft tissue, while the robot keeps the needle straight on a horizontal path (see Figure 2.6). Two silicon samples having different stiffnesses were used for the experiments. The samples were prepared using Smooth-Sil 910, which is a two-component silicone rubber: Part A is the base material that forms the product and Part B is the catalyst that hardens the silicon. For the softness adjustment, Silicon Oil was used. To prepare the samples, Parts A, B, and the oil were mixed in two different ratios, and the mixture was poured into cylindrical glass pots for molding. The diameter of the samples S1 and S2 is 45 mm and their heights are 35 and 20 mm, respectively.

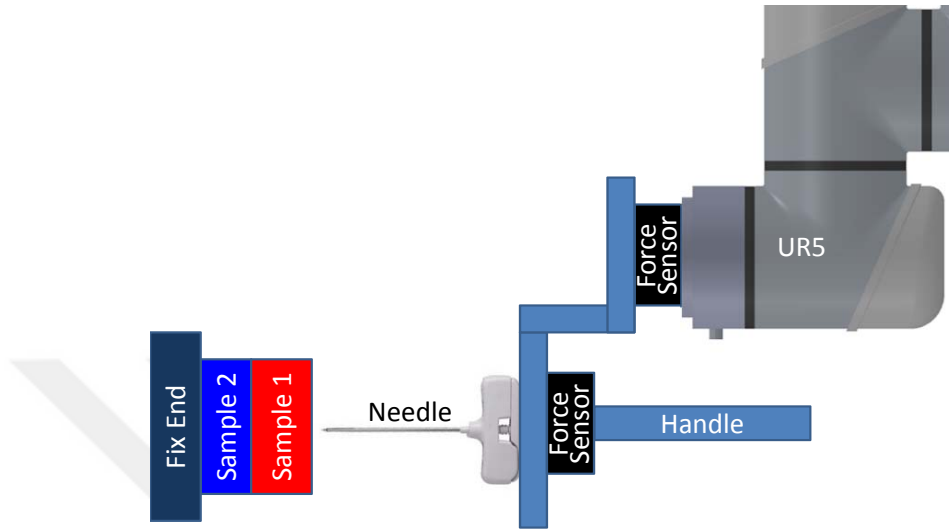


Figure 2.6: Experimental setup for needle insertion experiments.

2.4.1 Material Characterization of Silicon Samples

In order to characterize the material properties of the silicon samples, compression experiments were performed using a flat plate attached to the end-effector of the robot (see Figure 2.7a). The samples S1 and S2 were compressed to a depth of 10 mm and 2 mm, respectively, at a rate of 0.05 mm/s. The compression rate was kept low to reduce the influence of viscoelastic and inertial effects and obtain hyperelastic behavior of the samples. The force response was measured by the force sensor on the robot. We fitted a second order polynomial to force response vs compression depth data for better visualisation of the nonlinear elastic behavior of the silicon samples (Figure 2.7b). As shown in Figure 2.7b, S1 is much softer than S2.

2.4.2 Experimental Procedure

During the experiments, the subject inserted the needle into the samples S1 and S2, placed back to back as shown in Figure 2.6, at a rate of 5 mm/s (chosen in light of Podder et al. [2005]) until a depth of 45 mm was reached (i.e. ramp phase). Hence, the needle passed through the soft sample (S1) and partially penetrated into the stiffer one (S2). After the

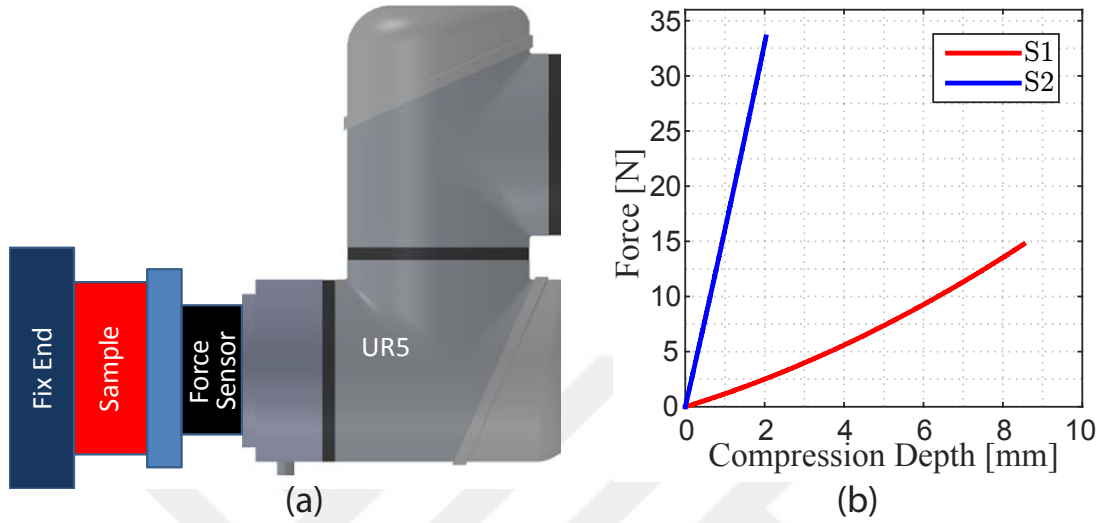


Figure 2.7: (a) Experimental setup for characterization of silicon samples, (b) force vs compression depth curves for two different samples.

desired depth was reached, the hold phase started, and then, the subject maintained the position of the needle at this depth for 10 seconds. A visual feedback showing the needle tip and a cursor moving with a speed of 5 mm/s was displayed to the subject through a computer screen, so that the subject inserted the needle at a relatively constant velocity during the ramp phase by following the motion of the visual cursor. The experiment was conducted for 3 different integration orders $\alpha = 0.4, 0.7$ (FOAC) and 1 (IOAC). The subject repeated the procedure 5 times for each integration order. For consistency with the parameters used in Section 2.3, admittance controller parameters are set to $m_F = 20 \text{ kgs}^{\alpha-1}$, $m_I = 20 \text{ kg}$, and $b_F = b_I = 25 \text{ Ns/m}$.

2.4.3 Data Collection and Metrics

For the experiment reported in Section 2.3, the contact environment was a linear spring having a constant coefficient. Hence, the human force was linearly dependent on the interaction force. However, in needle insertion task, the contact environment (i.e. silicon samples) exhibits nonlinear and layered behaviour. Moreover, as the needle passes through

the silicon samples, local stiffness changes as a function of penetration depth. Hence, the human force is not linearly dependent on the interaction force and has to be measured separately. For this reason, we modified the handle design and attached a second force sensor (Mini 40, ATI Inc.) to measure the force applied by human F_h directly (Figure 2.6). We use the similar metrics defined in Section 2.3.2 to quantify the human effort under different task conditions. Additionally, we would like to note that P^{ave} was calculated using directly F_h since it was measured by the additional force sensor.

2.4.4 Results

The performance metrics were calculated for the both phases (except A_P , which was evaluated for the hold phase only) of all trials. The means and the standard errors of the means are shown in Figure 2.8. End-effector position and velocity, interaction force, and force applied by human during an experimental trial are shown in Figure 2.9.

As shown in Figure 2.8a, average power consumed by human, P^{ave} , did not change with the integration order during the ramp phase, whereas it was much higher under IOAC than that of FOAC during the hold phase. Figure 2.8b shows that average force F_h^{ave} applied by human was similar for different values of integration order, but the oscillation amplitudes were quite different (Figure 2.8c). As shown in Figure 2.9d, human force fluctuated significantly during the hold phase of the task under IOAC ($\alpha = 1$). In fact, interaction force under IOAC oscillated even with a higher amplitude during the hold phase (Figures 2.8d and 2.9c). Average dominant frequency of oscillations in force applied by human, Ω_{F_h} , and interaction force, $\Omega_{F_{\text{int}}}$, increased as the integration order α decreased during both phases (Figures 2.8e and 2.8f). Average amplitude of oscillations in end-effector position A_P was higher under IOAC during the hold phase (Figure 2.8g). On the other hand, the change in the integration order did not affect A_P much under FOAC. We can observe that the amplitude of oscillations in interaction force, force applied by human, and end-effector position and velocity were larger under IOAC than that of FOAC during the hold phase (Figure 2.9).

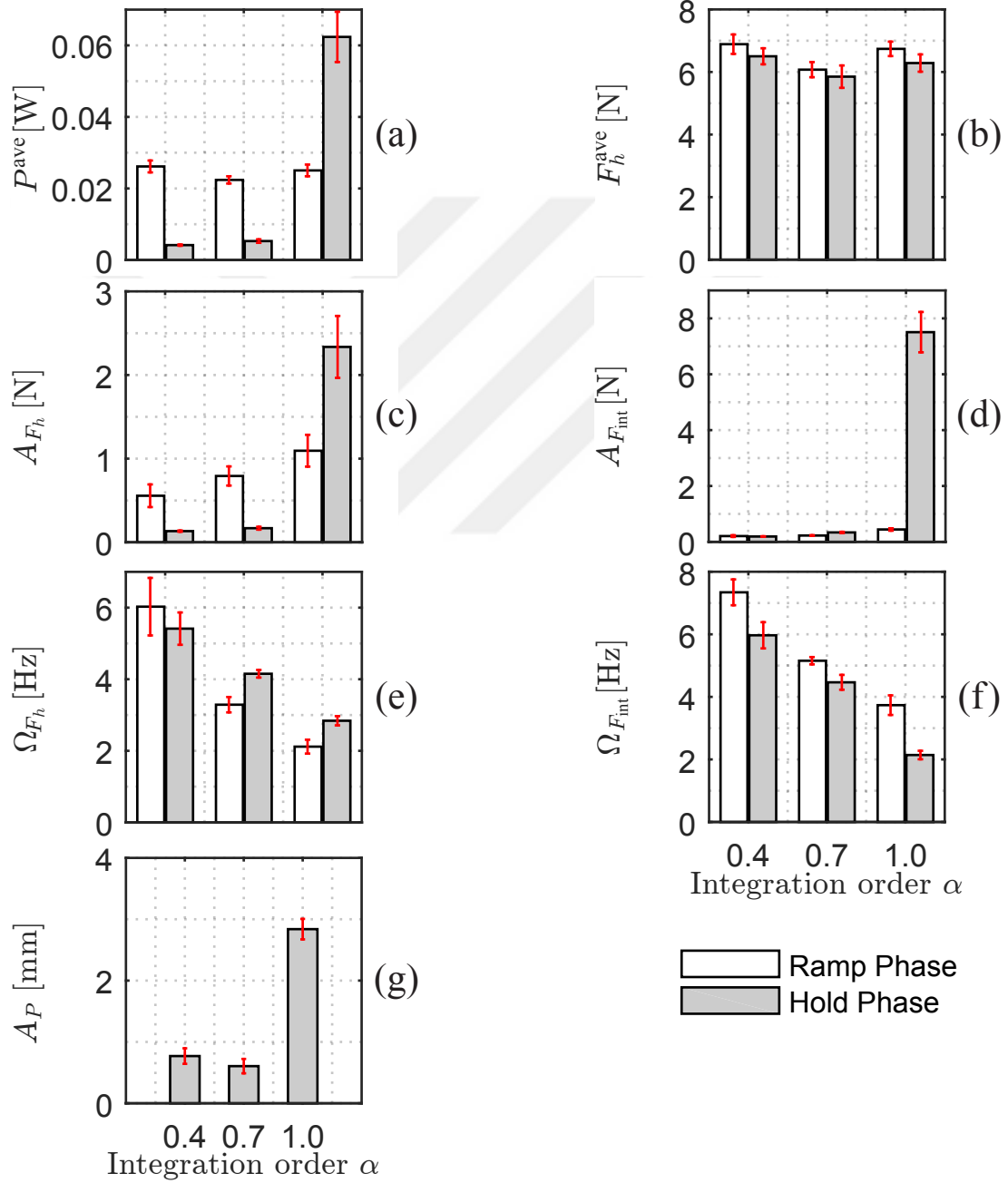


Figure 2.8: The means and the standard errors of means of normalized performance metrics for needle insertion experiment.

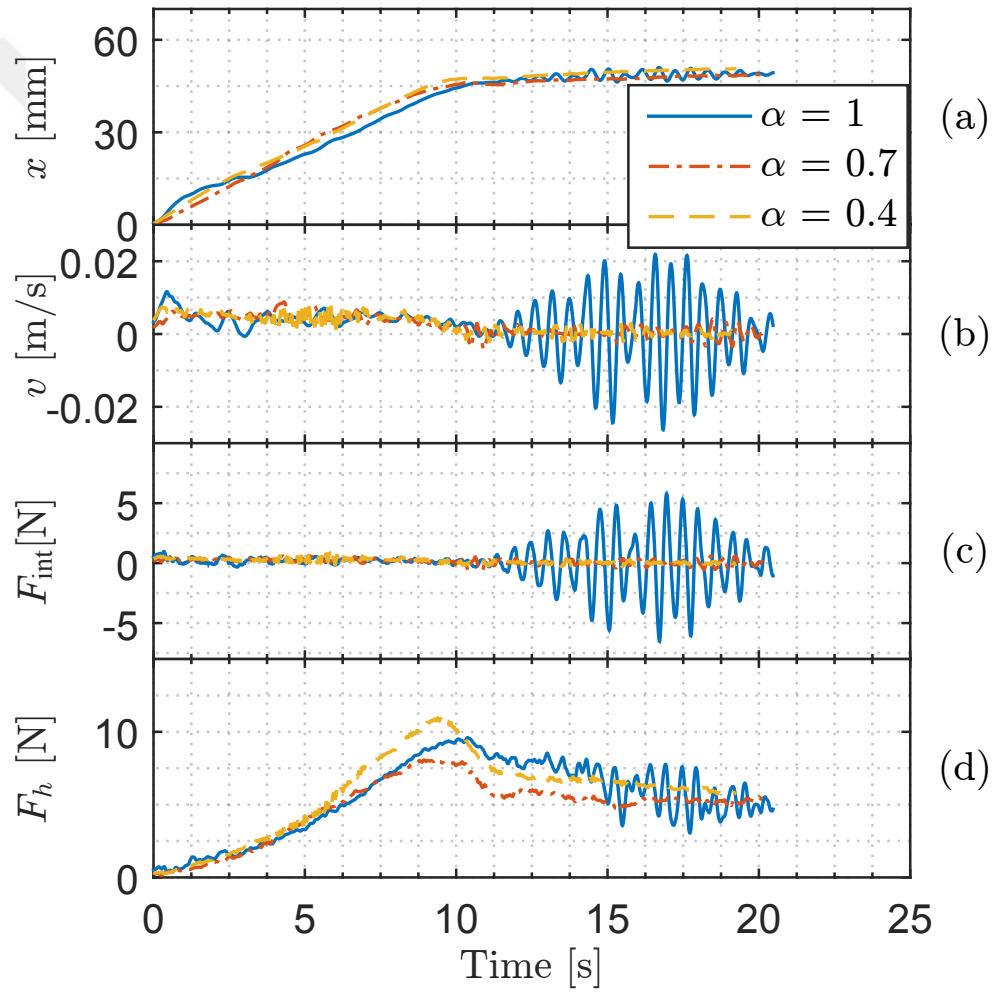


Figure 2.9: End-effector position x , and velocity v , interaction force F_{int} , force applied by human F_h as a function of time.

2.4.5 Discussion of the Experimental Results

During needle insertion, achieving higher target precision is required to avoid tissue damage [Podder et al., 2005]. Large oscillation amplitudes in force and position can cause larger deviations of needle tip from the target region. Furthermore, if needle is to be inserted into critical and sensitive regions in human body, undesirable motion of the needle should be avoided to reduce harming neighboring tissue. For instance, the epidural space in an adult lumbar spine is only 3-5 mm thick, and unintentional dural puncture, causing complications, may occur during epidural injection while operator attempts to identify the epidural space [Norris et al., 1989; Sprigge and Harper, 2008]. Our experiment shows that, compared to IOAC, FOAC is better in task precision since the fluctuations in needle tip were dampened (see Figure 2.9) more effectively during the hold phase. The position, velocity, and force profiles shown in Figure 2.9 were consistent in all insertion trials.

Similar to the experimental results reported in Section 2.3.4, frequency of oscillations in force slightly increased under FOAC (Figures 2.8e and 2.8f), but damping remained effective for larger range of frequencies (as anticipated from Figure 2.3c), and hence, needle tip oscillations were better absorbed (Figure 2.8g). Using IOAC with higher admittance damping would also reduce oscillations, but higher human effort would be required to insert the needle during the ramp phase under high admittance damping. On the other hand, FOAC displays frequency-dependent damping, which enforces higher effective damping for the high frequency components of interaction force (see Figure 2.3c).

The results of the needle insertion experiments show that human effort was reduced under FOAC. The power consumed by human did not change during the ramp phase for different values of integration order, while it was significantly reduced during the hold phase (Figure 2.8a). In general, reduction in amplitude of oscillations in force and end-effector position, as well as power consumed by human under FOAC during the hold phase is inline with the results of the first experiment reported in Section 2.3. Augmenting our control architecture given in Figure 2.1 by taking advantage of additional techniques such as force amplification [Lamy et al., 2010] may also be beneficial for further reducing the human effort. However, in our experiments, we did not utilize such additional methods

since our aim here is to show clearly that FOAC reduces the human effort and outperforms IOAC.

An experimental comparison of FOAC and IOAC is challenging since parameters of FOAC are not physically equivalent to those of IOAC. The controller parameters of FOAC can be mapped to parameters of IOAC through impedance matching at a particular frequency such that responses of two controllers can be compared. During the ramp phase of our experiments, subjects were asked to move the end-effector at a constant velocity, so the desired operating frequency of the motion is zero. Given that task frequency is zero, we performed impedance matching at this frequency, such that FOAC and IOAC parameters are set to be equal at this frequency, resulting in $m_F=m_I$ and $b_F=b_I$. Note that the value of admittance mass does not affect the response at zero frequency. Consequently, as the integration order changes, A_{F_h} , during the ramp phase, should not change ideally, but during the experiments changes are observed since users cannot maintain a perfectly constant speed. Moreover, A_{F_h} and A_P under these controllers differ more during the hold phase since FOAC dampens these oscillations more effectively.

2.5 Discussion

In this chapter, we showed potential advantages of FOAC over IOAC. Given the admittance controller affects the coupled system dynamics in a non-trivial manner, rendering analytical design methods infeasible, a computational approach is used to determine appropriate controller parameters for bounded human and environment impedances. Our computational approach resembles to the complementary stability analysis in Buerger and Hogan [2007]. The stability analysis, carried out for a bounded equivalent impedance, revealed that the stability robustness of control parameters to changes in human and/or environment stiffness is improved under FOAC.

In addition to the stability maps, we studied transparency, stability robustness, and task performance through two pHRI studies involving continuous contact with linear and non-linear environments. Under impedance matching, we analytically showed that the stability robustness under FOAC is higher than that of IOAC for any environment and human arm impedance. We also showed that FOAC provides advantages in terms of the transparency of the closed loop system. In particular, the computational analysis of the closed loop impedance of the coupled system revealed that the effective damping of the closed loop system under IOAC decays as the frequency increases. However, effective damping under FOAC increases up to a certain frequency, before it starts to decay. In other words, damping supplied to the coupled system under FOAC remains large for an extended range of frequencies. We showed that this frequency-dependent damping behavior of FOAC is beneficial for ensuring robust stability. Furthermore, our experimental results provided evidence that this behavior under FOAC enhanced human performance by absorbing vibrations during pHRI tasks involving physical interactions with linear and nonlinear environments.

Impedance matching analysis revealed that the parameters for FOAC maps to different parameters of IOAC at each frequency. The frequency dependent nature of FOAC is advantageous as it enhances the stability robustness of the system at high frequency ranges, while providing favorable transparency characteristics at low frequency ranges. Note that similar, and possibly more favorable, system responses can be achieved through the use of *adaptive* IOAC. However, as the controller parameters of such an adaptive controller would

be frequency dependent, an adaptive IOAC will not be LTI. As a result, methods/tools from the familiar linear systems theory would not be applicable for designing such controllers, significantly complicating their analysis. Hence, one of the main advantages of FOAC is the fact that it can provide frequency dependent controller parameters while its design/analysis can still be handled within the relatively simple LTI systems framework.



Chapter 3

A MULTI-CRITERIA OPTIMIZATION FRAMEWORK FOR INTERACTION CONTROLLER DESIGN

3.1 Computational Multi-Criteria Design Framework

Stability robustness and performance analyses of an interaction control system are challenging, as the standard tools used for servo control cannot be applied. In particular, as noted by Buerger and Hogan [2007], two fundamental differences exist for interaction control systems: the closed-loop stability and performance cannot be predicted and characterized using the open-loop transfer function alone, and the controller parameters do not directly affect the stability and performance of the coupled system. Consequently, there exists no straightforward way to investigate the stability and performance of such systems analytically, while computational approaches have been shown to provide promising results [Buerger and Hogan, 2007; Hulin et al., 2014; Labrecque and Gosselin, 2018]. It is also important to note here that the use of fractional order controllers makes any form of analytical analysis even more challenging.

Buerger and Hogan [2007] used a computational loop shaping approach where they treated stability and performance separately and optimized an interaction controller for maximum performance while satisfying a stability constraint. In the controller parameter space, which corresponds to all possible combinations of controller parameters that are studied, the stability of the closed-loop system is evaluated, and a set of controller parameters that yields to the maximum performance among the stable sets is found. Although this approach accounts for the multiple design objectives, it is broadly classified under scalarization based optimization approaches, where a multi-criteria optimization problem is solved by transforming it into a series of single objective problems. Such approaches

either aggregate multiple objectives into a single objective function using fixed weights, or prioritize one and optimize the other objectives over the solutions of the prioritized one. The prioritization of one objective over others is the method followed in the computational loop shaping approach [Buerger and Hogan, 2007] where a preference between objectives are set and each objective is optimized sequentially, before having a thorough knowledge on the tradeoff between the objectives. The solutions obtained with such sequential approaches are, in general, sub-optimal. On the other hand, assigning proper weights to aggregate the objectives into a single objective for optimization is also a problem-dependent and non-trivial task, thus, scalarization techniques, in general, fall short of providing a general framework for optimal controller design under multiple design objectives.

In this dissertation, we propose Pareto methods for multi-criteria optimization of interaction controllers where the solutions obtained with Pareto methods are truly optimal, unlike sub-optimal solutions provided by scalarization based methods. Moreover, Pareto optimization allows the designer to study the tradeoff between transparency and stability robustness thoroughly and inspect all possible sets of optimal solutions among which an informed decision can be made.

The impedance that human feels during the interaction with environment has critical importance in pHRI tasks. For instance, in a robotic assisted surgery, the control architecture for the interaction should ensure that the impedance of soft tissue (i.e. environment) is reflected to surgeon so that she/he can operate on patient more effectively. In such a case, the surgeon desires to feel the environment impedance (i.e. desired impedance) alone, and not the robot's impedance. Alternatively, in a different task, human may wish to move the robot in free space, where she/he does not desire to feel any dynamics coming from the robot. Therefore, depending on the task, a transparency metric can be defined based on the desired and reflected impedance to human.

In addition to the stability constraint and the transparency metrics, it is useful to define a suitable robustness metric in order to inspect the tradeoff between stability robustness and transparency, as stability information alone does not provide much insight.

Using the transparency and stability robustness metrics, a multi-criteria optimization

problem to be solved using Pareto methods can be formed. All the optimal solutions obtained by this method constitute the Pareto front and different solutions on the Pareto front represent different preferences between these metrics. Once the Pareto front is obtained, one can further study the solutions under the light of additional information and requirements regarding the task. With this study, an informed decision can be made to finalize the controller design by selecting an optimal solution from the Pareto set. Once an informed decision on the optimum objectives is made, the corresponding optimal set of controller parameters can be determined easily.

Along these lines, we modify and augment the computational loop shaping approach for multi-criteria optimization. Assuming an LTI model of the robot is available and the type of LTI controller to regulate the interaction between the robot and the human is selected, the following steps are followed to optimize the controller parameters for a robust and transparent design.

1. For each parameter of the interaction controller, a range of values is chosen and discretized.
2. A metric for transparency is defined and transparency is evaluated for each set of controller parameters.
3. A metric for robustness is defined and robustness is evaluated for each set of controller parameters.
4. Pareto front is constructed by considering the transparency and robustness objectives.
5. Informed decision on the set of optimal solutions is made after inspecting the Pareto front and imposing additional constraints on the robustness and transparency requirements as well as other criteria considering the pHRI task.

The Pareto optimization approach for the multi-criteria optimization problem opens door to rewarding results. The first outcome of the Pareto optimization approach is the design of an optimal interaction controller. The second outcome of the Pareto optimization

approach is that it enables fair comparison of interaction controllers having different types, structures, and parameters of different physical interpretations. For such different interaction controllers, the relation between Pareto fronts of each one provides a fair assessment of the optimal performance of each controller.

In this dissertation, as case studies, interaction controller designs under the forms of FOAC and IOAC are provided to materialize the design framework and investigate the interpretation of Pareto front curve from an interaction controller design point. The considered pHRI scenarios and the step 1 of the design framework are presented in Section 3.2, objective functions for transparency and robustness (steps 2–3) are presented in Section 3.3, and the multi-criteria design of the interaction controller (steps 4–5) is presented in Section 3.4.

3.2 Case Study: Interaction Controller Design for a pHRI Application

3.2.1 The pHRI Task

As a case study to present the computational optimization framework to design an interaction controller, three different pHRI scenarios are considered. First scenario is that human and robot physically interact with each other excluding environment where human desires to move the robot without any resistance. Second scenario includes a nominal environment where robot interacting with human is in continuous contact with. In the third scenario, the dynamics of the environment changes. Note that the first scenario is used to establish a baseline for the design as any pHRI task requires at least human and robot to interact with each other.

To regulate a physical interaction between human and robot, impedance/admittance based controllers have been widely used [Hogan, 1984]. An impedance controller computes forces to be applied by a robot for an imposed motion, while an admittance controller computes the trajectory to be followed by a robot under the action of forces applied. In general, it is more natural to utilize admittance control when robots used in pHRI tasks do not possess high backdrivability. Such robots are usually motion controlled; hence, the interaction force between human and robot serves as the input to an admittance controller that generates velocity references for the motion controller of the robot. In our case study, we use an admittance controller architecture for the optimization. However, the procedure for the proposed optimization framework is sufficiently general, hence applying it to other interaction controller architectures such as impedance controllers is quite straightforward. In a typical implementation for pHRI, an admittance controller regulates the dynamics of the interaction through a linear admittance model that consists of inertial and dissipative elements. Spring elements are not preferred for collaborative manipulation tasks as they force the robot to return to an equilibrium position, which is typically not desirable.

3.2.2 The Closed-Loop System

Two interaction controllers will be considered in the upcoming analyses to demonstrate the proposed approach: fractional order admittance controller (FOAC) and, a special form of it, integer order admittance controller (IOAC). In these analyses, the admittance control architecture introduced in Section 2.1.2 is utilized (see Figure 2.1).

As already mentioned in Chapter 2, FOAC is based on fractional order calculus, a generalization of the well-known integer order calculus and allows differentiation and integration of arbitrary orders. Fractional order calculus has been successfully utilized in other application areas in the past [Ayyildiz et al., 2014; Tokatli and Patoglu, 2015, 2018; Tokatli, 2015]. In Chapter 2, we have shown that fractional order admittance controllers (FOAC) can be applied to pHRI systems as well [Aydin et al., 2017, 2018].

FOAC used in this case study has the same form given in Equation (2.5). As the unit of m_F is $[\text{kg s}^{\alpha-1}]$, the physical interpretation of it changes depending on the integration order α , whereas the unit of b_F is always $[\text{Ns/m}]$ (see Equation (2.5)). However, note that the damping of FOAC is not equivalent to b_F . The effective mass and damping provided by FOAC are $m_F \omega^{\alpha-1} \sin(\frac{\alpha\pi}{2})$ $[\text{kg}]$ and $b_F + m_F \omega^\alpha \cos(\frac{\alpha\pi}{2})$ $[\text{Ns/m}]$, respectively, where ω is the frequency [Tokatli and Patoglu, 2015, 2018; Aydin et al., 2018].

Thanks to the analytical nature of the fractional order differintegration, as the integration order is decreased gradually from 1 to 0, the inertial energy storage characteristics of the controller decay and energy dissipation characteristics dominate. For $\alpha = 0$, the controller acts like a pure damper. On the other hand, when the integration order is $\alpha = 1$, FOAC is equivalent to IOAC as m_F is equivalent to pure mass.

Knowing that the structure of an admittance controller is different for each integration order α , a fair comparison is challenging as each one has a different physical interpretation. Therefore, to investigate the tradeoff between stability robustness and transparency under various integration orders thoroughly by using the optimization framework proposed in this study is a rewarding practice.

In this study, the Grunwald-Letnikov definition is used for calculation of fractional order differintegrals, since this definition enables easier implementation in discrete time

domain [Chen et al., 2009]. More information on the chosen differintegral and its computational details can be found in Tokatli and Patoglu [2015, 2018]; Aydin et al. [2017, 2018].

3.2.3 LTI Models of Robot, Human Arm, and Environment

3.2.3.1 Robot and Sensor Model:

For the experimental validation of the proposed optimization approach, a UR5 robot (Universal Robots Inc.) is used to perform a pHRI task. The dynamic model of the robot is needed for the interaction controller design which was already obtained experimentally (see Equation (2.7) in Section 2.1.3.1).

The same model given by Equation (2.8) in Section 2.1.3.2 is used to describe the dynamics of the force sensing.

3.2.3.2 Human Arm and Environment Impedance:

For the computational analyses of transparency and stability robustness, the LTI models described by Equations (2.9) and (2.10) are used for human arm and environment impedances, respectively (see Section 2.1.3.3 for details). In our analyses, we combine human arm and environment impedance, and investigate the stability robustness to variations in the components of the equivalent impedance. As mentioned in Section 2.1.3.3, the equivalent impedance used in our study is $Z_{eq}(s) = \frac{m_{eq}s^2 + b_{eq}s + k_{eq}}{s}$, where equivalent stiffness, damping, and mass become $k_{eq} = k_h + k_e$, $b_{eq} = b_h + b_e$, and $m_{eq} = m_h + m_e$, respectively.

The bounds of the equivalent impedance for each scenario considered in this study are following. For the first scenario, when there is no contact interaction with environment, only the bounds of the human arm impedance is considered. Lower and upper bounds for the human arm stiffness are taken as 0 (when human is not in contact with the end-effector of the robot) and 600 N/m [in light of Dolan et al., 1993; Tsuji et al., 1995], respectively. Moreover, the lower and upper bounds for the mass parameter are 0 (which happens when human releases her/his contact) and 5 kg, respectively, whereas the interval for the damping

is between 0 and 41 Ns/m [Dolan et al., 1993; Tsuji et al., 1995]. Note that, the bounds for the k_{eq} correspond to 0 and 600 N/m.

For the second scenario, the contact interaction with environment is considered where environment is modeled by a spring alone having a stiffness of k_e . Therefore, the damping, and the mass of the equivalent impedance are the same as damping and mass of human arm, respectively, so that $b_{eq} = b_h$, and $m_{eq} = m_h$. The environment is assumed to have a nominal stiffness of 610 N/m, thus the range for the equivalent stiffness is $610 \text{ N/m} \leq k_{eq} \leq 1210 \text{ N/m}$.

For the third scenario, the environment stiffness is assumed to change between the nominal value ($k_e = 610 \text{ N/m}$) and $k_e \leq 1010 \text{ N/m}$. So, the range for environment stiffness is $610 \text{ N/m} \leq k_e \leq 1010 \text{ N/m}$, thus, the range for the equivalent stiffness is $610 \text{ N/m} \leq k_{eq} \leq 1610 \text{ N/m}$ for the third scenario. In the following transparency and stability robustness analyses, these exemplary pHRI scenarios are considered.

3.3 Objective Functions

In this section, the transparency and stability robustness objectives used for the controller design are introduced for the pHRI system.

3.3.1 Transparency

This section investigates the effective closed-loop impedance of our pHRI system and provides insight on transparency under FOAC and IOAC. The difference between the desired impedance, $Z_{\text{des}}(s)$, and the effective impedance reflected to human, $Z_{\text{disp}}(s)$ (see Equation (2.11)), can be written as:

$$\Delta Z(s) = Z_{\text{des}}(s) - Z_{\text{disp}}(s) \quad (3.1)$$

which we call as the parasitic impedance.

As long as the parasitic impedance, $\Delta Z(s)$, is small (large), then the transparency of the coupled system is high (low). For the controller design, we analyze the transparency of the coupled system under the assumption that human desires to feel the environment as in a robotic assisted surgery scenario. Therefore, desired impedance is the environment impedance, $Z_{\text{des}}(s) = Z_e(s)$, which will be used for the analyses. Using Equations (2.11) and (3.1), the magnitude of parasitic impedance in frequency domain, $|\Delta Z(j\omega)|$, is:

$$|\Delta Z(j\omega)| = 1/|G(j\omega)Y(j\omega)H(j\omega)| \quad (3.2)$$

Clearly, maximizing $|GYH|$ minimizes $|\Delta Z|$, which in turn maximizes the transparency. Furthermore, we can deduce that maximizing the magnitude of $Y(j\omega)$ is required to improve the transparency. From Equation (2.5), the denominator of the $Y(j\omega)$ can be obtained as $Z_{\text{FOAC}}(j\omega) = m_F(j\omega)^\alpha + b_F$ where minimization of the magnitude of it is sufficient to maximize the magnitude of $Y(j\omega)$. So, the magnitude of $Z_{\text{FOAC}}(j\omega)$ is minimized as well as that of $Z_{\text{IOAC}}(j\omega)$ (for the case of IOAC, i.e. the special form of FOAC for $\alpha = 1$). Minimization of $|Z_{\text{FOAC}}(j\omega)|^2$ and $|Z_{\text{IOAC}}(j\omega)|^2$ is sufficient for this purpose, where

$$|Z_{\text{FOAC}}|^2 = m_F^2 \omega^{2\alpha} + b_F^2 + 2m_F b_F \cos\left(\frac{\pi\alpha}{2}\right) \omega^\alpha \quad (3.3)$$

$$|Z_{\text{IOAC}}|^2 = m_F^2 \omega^2 + b_F^2 \quad (3.4)$$

As expected, lower values of m_F , and b_F result in higher transparency. Especially at lower frequencies, effect of b_F is more dominant on parasitic impedance. So, lower values of b_F are more desirable for higher transparency at low frequencies. Moreover, effects of α , and m_F become more dominant at higher frequencies, and lower values of m_F are also more desirable for higher transparency at high frequencies.

Inspecting the magnitude of $Y(j\omega)$ alone gives information about how controller parameters affect the transparency. However, for more conclusive results, parasitic impedance function should be inspected since the robot itself contributes to the parasitic impedance as well. The fact that the contributions of controller and robot on parasitic impedance change as functions of frequency calls for a quantitative metric for parasitic impedance. A proper one was defined by Buerger and Hogan [2007] which computes it for a discrete range of frequencies. Adopting that cost function, the following measure for parasitic impedance cost is defined

$$C = \sum_{\omega_L}^{\omega_U} W(\omega) \log |\Delta Z(j\omega)| \quad (3.5)$$

where $W(\omega)$ is a weight function which can be used to adjust the contribution of each frequency. In addition, ω_L and ω_U are the lower and upper boundaries of the frequency range, respectively. In this study, a logarithmically spaced frequency range varying from 0.01 to 30 Hz is chosen for the discretization of the parasitic impedance function. The magnitude of a fifth order butterworth filter having a cutoff frequency of 5 Hz is used as a weight function to boost the effect of low frequency content on the parasitic impedance cost and reduce the contribution of higher frequencies as the frequency range of human voluntary movements is limited [Brooks, 1990; Dimeas and Aspragathos, 2016]. Thus, achieving lower parasitic impedance for higher transparency is more desirable at lower frequencies. Using

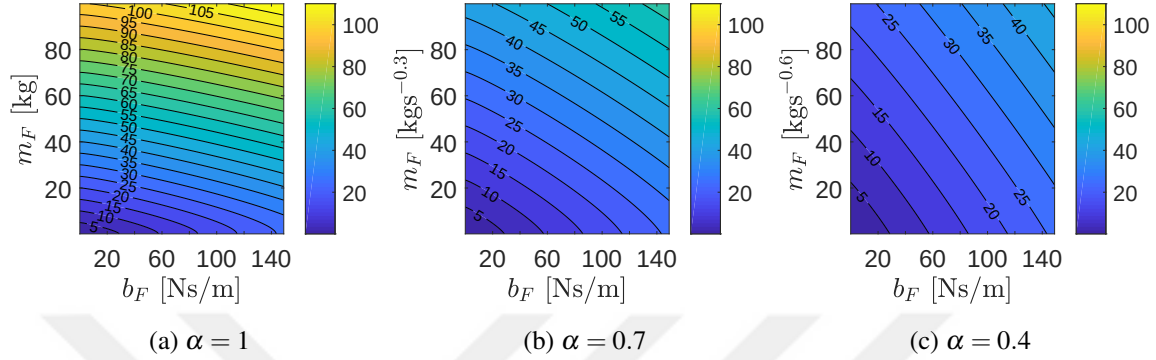


Figure 3.1: Parasitic impedance cost maps of our pHRI system under (a) IOAC $\alpha = 1$, (b) FOAC $\alpha = 0.7$, and (c) FOAC $\alpha = 0.4$.

Equation (3.5), parasitic impedance cost for each set of controller parameters is evaluated, and the resulting parasitic impedance cost maps are constructed (Figure 3.1). As expected, lowering m_F , and b_F reduce the parasitic impedance cost, leading to higher transparency.

Although the value of the parasitic impedance cost, so as the level of transparency, for a given set of controller parameters is not influenced by the environment impedance, using lower controller gains to achieve higher transparency may not be feasible due to the stability constraints and robustness needs. In the following sections, 3.3.2.1 and 3.3.2.2, stability and stability robustness analyses are presented, respectively.

3.3.2 Robust Stability

3.3.2.1 Stability

In this section, stability analysis which provides a basis for the robustness analysis is presented.

Considering the boundaries of equivalent impedance, the stability characteristics of the coupled system is analyzed using stability maps. As mentioned in Section 2.2.1, a stability map is a graphical representation of the controller parameters for which the resulting closed-loop system becomes stable for a range of environment/human arm impedances.

The stability analysis is performed by numerically studying the location of the closed-loop poles of the system. This requires some knowledge on the dynamics of the human arm and the environment, which is not easy to obtain due to uncertainties in these. Although the exact dynamics of human arm and environment are uncertain, their behavior typically resides within specific limits. For this reason, a computational approach for designing a pHRI controller should focus on the boundaries of the parameter space of the combined impedance for human arm and environment interacting with the robot. If a controller can guarantee stability on the entire boundary, it can ensure stability within this space for all interaction dynamics [Willaert et al., 2011]. In fact, this is the approach followed in this study for evaluating the stability under a given set of controller parameters.

The search for a stable set of controller parameters is relatively straightforward when the admittance controller is of integer order. However, when a fractional order element is used in the control loop, the resulting characteristic equation no longer takes a polynomial form; hence, the stability analysis becomes more involved as discussed in Section 2.2.1. For fractional order systems that are of commensurate order, checking the stability of the system with a non-polynomial characteristic equation can be accomplished by performing a transformation from the fractional order domain to the integer order domain. According to Matignon's theorem [Matignon, 1998; Chen et al., 2009], the resulting integer order system possesses equivalent stability characteristics as the fractional order system.

In Figure 3.2, the stability maps for FOAC ($\alpha = 0.4$ and 0.7), and IOAC ($\alpha = 1$) are depicted. These maps are generated considering the bounds for the equivalent impedance in the first pHRI scenario given in Section 3.2.3.2, where human and robot interacts alone and no contact interaction with environment is involved. Note that in this scenario, the upper limit for k_{eq} is set to be the maximum value of human arm stiffness reported in Dolan et al. [1993]; Tsuji et al. [1995]. It is a valid assumption that mass and damping parameters of human arm impedance may not change drastically during the execution of a pHRI task. However, it is difficult to know their exact values in practice. Moreover, in case human releases her/his contact with the end-effector of the robot at any instant during the interaction, the mass and damping contribution of human arm reduces to zero which may destabilize

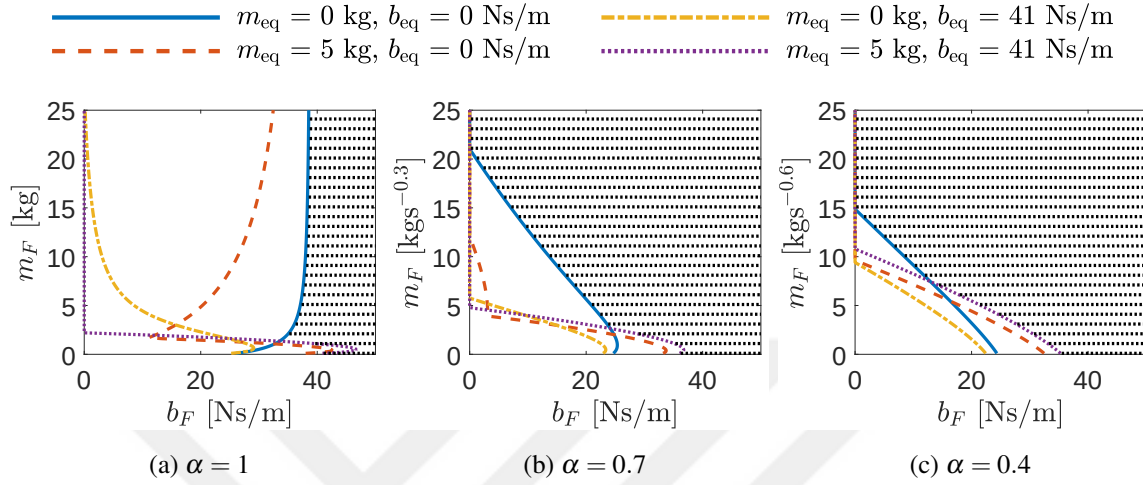


Figure 3.2: Stability maps of our pHRI system for $k_{eq} = 600$ N/m under (a) IOAC $\alpha = 1$, (b) FOAC $\alpha = 0.7$, and (c) FOAC $\alpha = 0.4$. The curves represent the stability boundaries for different combinations of extreme values of m_{eq} , and b_{eq} . The shaded regions show the sets of admittance parameters that ensure stability for all combinations of extreme bounds of m_{eq} , and b_{eq} .

the system. So, in our controller design process, for a practical implementation, the bounds for m_h and b_h are considered and taken into account in m_{eq} and b_{eq} , respectively.

Figure 3.2a depicts the stability map under IOAC for $k_{eq} = 600$ N/m. As one can observe, the value of the b_F required to stabilize the system gets higher (lower) under high (low) m_F as m_{eq} reduces. In other words, it is easier (more difficult) to stabilize the system under low (high) m_F as m_h reduces. Knowing that the exact value of m_{eq} is uncertain due to the lack of knowledge on m_h , any decrease (increase) in the mass contribution of human arm can easily destabilize the system if m_F of the controller is already set to some high (low) value. For instance, let's assume that controller parameters are already chosen as $m_F = 5$ kg and $b_F = 30$ Ns/m, considering the upper bound of m_{eq} only. If human releases her/his contact with the end-effector, the stable region shrinks, and this parameter set shifts to the unstable region, so the stability of the coupled system is jeopardized. To prevent such an undesired possibility from happening, a designer should consider these effects.

Moreover, it is widely accepted that b_{eq} contributes to the stability favorably [Colgate et al., 1993; Colgate and Brown, 1994; Colgate and Schenkel, 1997; Weir and Colgate, 2008], thus, only the lower bound of b_{eq} , which is 0, is considered as the worst case in earlier studies. However, Willaert et al. [2011] presented several examples where larger b_{eq} may destabilize the system under specific conditions, though the system is stable for $b_{eq} = 0$. Indeed, our results illustrate such a case, as well. For instance, let's assume that controller parameters are set to $m_F = 0.5$ kg and $b_F = 45$ Ns/m considering $b_{eq} = 0$ only as the worst case for the equivalent damping. However, an increase in the physical damping easily destabilizes the system since the lowest allowable value for b_F is 48 Ns/m when the equivalent damping in the system increases to its maximum (Figure 3.2a). Therefore, the upper bound of the physical damping in the equivalent impedance should be considered in addition to the lower bound of it as well to guarantee stability. Note that this counter intuitive effects of b_{eq} are also valid and should be considered under FOAC (Figures 3.2b and 3.2c).

Along these lines, a controller parameter set which makes the system stable under all combinations of extreme bounds of m_{eq} and b_{eq} is considered as a stable set of parameters, as suggested in [Willaert et al., 2011], so that any change in m_{eq} and b_{eq} can be tolerated. In light of these, shaded areas are accepted as the stable regions in Figure 3.2. Note that, allowable values of b_F under FOAC are lower than those of IOAC. As lower values for b_F are more desirable to attain higher transparency at low frequencies, where the effect of m_F and integration order α on transparency is minimal, evidence already suggests that FOAC can offer a better tradeoff between stability and transparency, though robustness analyses should be performed for conclusive results. We extend these stability regions to analyze the stability robustness to reach more conclusive results on this tradeoff.

3.3.2.2 Robustness

The dynamical behavior of a pHRI system is subject to high uncertainty, so that the controller parameters need to be selected carefully to ensure robust stability. Due to the fact that our stability maps rely on an approximate dynamical model and the bounds set for en-

environment/human arm impedance, more information on the sensitivity of the system under each set of controller parameters is needed for a robust design. For instance, designing a controller to stay exactly on the stability boundary could be dangerous as small perturbations in the environment impedance can easily destabilize the system, though, being close to this boundary is more desirable for attaining higher transparency. However, it is difficult to know how close we should be to this boundary since how much variation in the environment and human arm impedances, and other perturbations and disturbances, which may act on the closed loop system, that controller can tolerate are not known a priori.

As a remedy for this problem, we propose to use stability robustness maps in this study. These maps are more informative than the stability maps as they provide the degree of stability, in other words, information on how robust the system is. In order to construct a robustness map, a measure for robustness is needed.

In Chapter 2, we utilized the vector margin, the inverse of the maximum magnitude of loop sensitivity function $S(s)$ [Åström and Murray, 2010], as an indicator of the stability robustness for LTI systems. Using Equation (2.17), the sensitivity function $S(s)$ in frequency domain for our system can be defined as

$$S(j\omega) = \frac{1}{1 + L(j\omega)} \quad (3.6)$$

where $L(j\omega) = G(j\omega)Y(j\omega)H(j\omega)Z_{eq}(j\omega)$ denotes the loop transfer function. From this equation, one can note that a larger loop gain reduces the magnitude of the sensitivity function and leads to a more robust system. Then, the vector margin (i.e. robustness margin) can be defined as

$$\rho = \frac{1}{\max(|S(j\omega)|)} \quad (3.7)$$

where $\max(|S(j\omega)|)$ represents the maximum magnitude of the loop sensitivity function, $S(j\omega)$. The robustness margin is evaluated for the stable regions of the stability maps (Figure 3.2) to construct robustness maps.

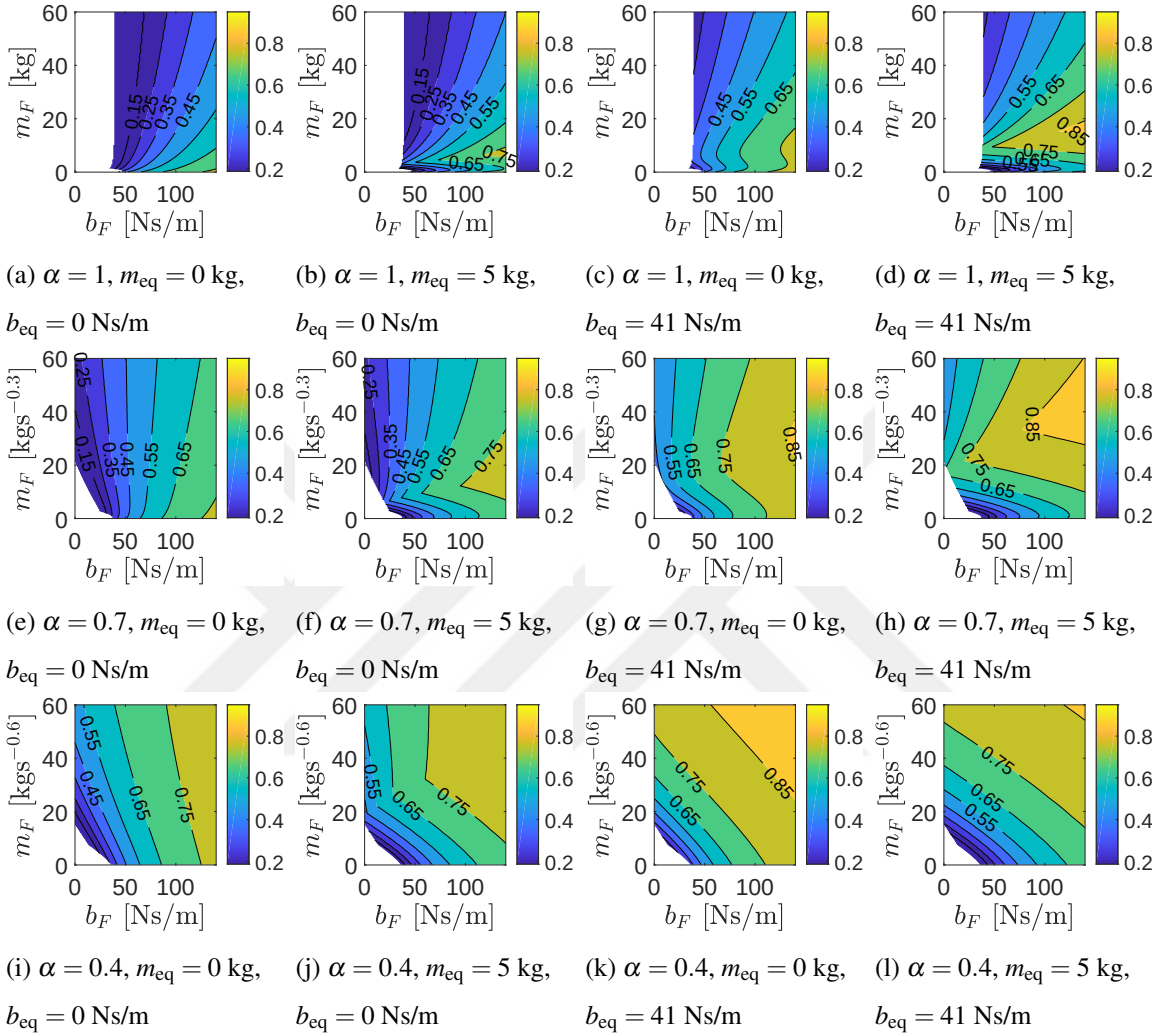


Figure 3.3: Robustness maps of our pHRI system for $k_{eq} = 600$ N/m under IOAC $\alpha = 1$, FOAC $\alpha = 0.7$, and FOAC $\alpha = 0.4$.

Three sets of robustness maps for $\alpha = \{1, 0.7, 0.4\}$, respectively, are created. The robustness maps are constructed for the stable regions of controller parameters for the first pHRI scenario given in Section 3.2.3.2 where human and robot interacts alone and no interaction with environment is involved, so this case could be treated as a baseline when pHRI involves a possible interaction with some environment. Constructing these maps for involvement of different environments (so higher values of equivalent stiffness) is not needed as these robustness maps already provide information on the robustness margin (Figure 3.3). Hence, one can easily deduce the degree of robustness for a set of controller parameters by inspecting these maps.

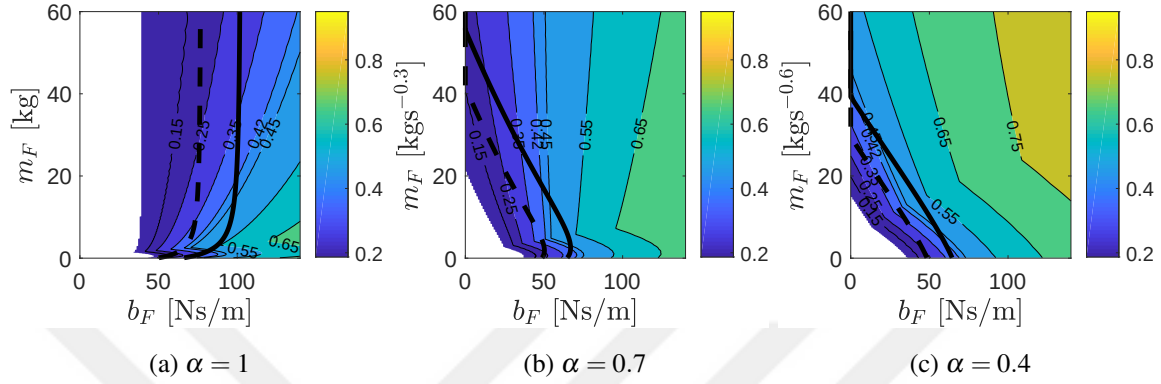


Figure 3.4: Refined robustness maps of our pHRI system for $k_{eq} = 600$ N/m under (a) IOAC $\alpha = 1$, (b) FOAC $\alpha = 0.7$, and (c) FOAC $\alpha = 0.4$. Solid and dashed, thickened black curves show the stability boundaries for $k_{eq} = 1210$ N/m and $k_{eq} = 1610$ N/m, respectively.

For each integration order, four different robustness margins are calculated for each parameter set, one for each combination of extreme values of equivalent mass, m_{eq} , and damping, b_{eq} . As one can see, having no m_{eq} reduces (improves) the robustness under high (low) m_F whereas having some m_{eq} reduces (improves) the robustness under low (high) m_F . Moreover, counter intuitively, having no b_{eq} reduces (improves) the robustness under high (low) m_F whereas having some b_{eq} reduces (improves) the robustness under low (high) m_F (see Section 3.3.2.1 for detailed discussion on this). Thus, for a controller parameter set, the minimum of the robustness margins calculated for the four combinations of extreme values of m_{eq} and b_{eq} is taken as the *conservative* robustness margin, so that the worst cases for uncertainties in m_{eq} and b_{eq} are accounted for in the refined robustness maps.

In Figure 3.4, refined robustness maps under each integration order of interest are illustrated. The relation between the robustness margin and how much increase in equivalent stiffness can be tolerated is illustrated by the second and third scenarios given in Section 3.2.3.2; we have a maximum increase of 610 N/m, and 1010 N/m in equivalent stiffness for the second and third pHRI scenarios, so, the maximum expected equivalent stiffness value is $k_{eq} = 1210$ N/m, and $k_{eq} = 1610$ N/m, respectively.

Employing the principles for constructing the stability maps introduced in Section

3.3.2.1, stability boundaries for $k_{eq} = 1210$ N/m and $k_{eq} = 1610$ N/m are computed and superimposed on top of the robustness maps given in Figure 3.4. Using Figure 3.4a, we observe that, among the controller parameter sets laying on the stability boundary for $k_{eq} = 1210$ N/m ($k_{eq} = 1610$ N/m) under IOAC, the most robust set is the one having the robustness margin value of $\rho = 0.42$ ($\rho = 0.55$). In other words, any controller parameter set of IOAC having $\rho = 0.42$ ($\rho = 0.55$) ensures the robust stability for the bounds given for environment and human arm impedances in the second (third) pHRI scenario. Any controller parameter set of FOAC ($\alpha = 0.7$ and 0.4) having the same robustness margin $\rho = 0.42$ ($\rho = 0.55$) also maintains the stability up to $k_{eq} = 1210$ N/m ($k_{eq} = 1610$ N/m) (Figures 3.4b and 3.4c). Note that sets of controller parameters for FOAC having the robustness margin of $\rho = 0.42$ ($\rho = 0.55$) can tolerate equivalent stiffness values larger than $k_{eq} = 1210$ N/m ($k_{eq} = 1610$ N/m) as all of these sets lay slightly further away from the stability boundary.

Robustness maps show that as integration order decreases, lower admittance damping, b_F , values can be used for higher robustness (Figure 3.4). Considering the facts that effect of m_F and integration order α on transparency is minimal at lower frequencies and lower b_F is more desirable for higher transparency, robustness maps provide strong evidence that FOAC can offer a better tradeoff between transparency at low frequencies and stability robustness, which supports our earlier findings reported in Chapter 2.

Since FOAC and IOAC utilize control parameters having different physical interpretation, a direct comparison is not feasible [Aydin et al., 2018]. For a fair comparison, a multi-criteria optimization will be performed for each integration order to maximize the transparency and stability robustness objectives. Then, a conclusive result can be reached, after comparing the optimal controllers under each integration order.

3.4 Pareto Optimization

Due to the tradeoff between stability robustness and transparency, there is no set of controller parameters that can maximize both objectives at the same time. For this reason, a multi-criteria optimization involving robustness and transparency objectives is implemented using Pareto methods.

For a general multi-criteria optimization problem, all non-dominated set of solutions constitute the Pareto front which is a curve, surface, or hypersurface for the cases of two, three, or more objectives, respectively [Papalambros and Wilde, 2000; Marler and Arora, 2010]. All optimization criteria are treated simultaneously on the Pareto front, and the decision making is carried out after having a thorough knowledge of the system and its performance. Hence, Pareto methods provide more insight to the optimization problem, and the designer can make an informed decision by studying a wide range of options on the Pareto front [Unal et al., 2008].

There are several methods to obtain the Pareto front: Design Space Exploration and Pareto Filtering [De Weck, 2004], Weighted Sum Approach with weight scanning [Marler and Arora, 2010], Adaptive Weighted Sum [Kim and De Weck, 2006], Normal Boundary Intersection [Das and Dennis, 1998], Multi-objective Genetic Algorithms [Fonseca and Fleming, 1993], and Multi-objective Simulated Annealing [Serafini, 1994]. In this study, we utilize the weighted sum approach (with weight scanning) to obtain the optimal solutions by combining transparency and stability robustness objectives into a single cost function where the weight of each objective on the optimization is adjusted by a scalar. By performing the multi-criteria optimization under all weight combinations, Pareto front curve is obtained. Note that the Pareto front is also verified by finding non-dominated sets of objectives using another Pareto method: Design Space Exploration and Pareto Filtering. Since we did not observe any significant difference between the outcomes of these methods, we present the simpler method for the clarity of the presentation. For more details on the other method, the reader is referred to De Weck [2004] and Kim and De Weck [2006].

As the main objective in our study is to improve both robustness and transparency, we minimize the parasitic impedance cost, C , while maximizing the value of the robustness

margin, ρ . To eliminate the scale difference between the two metrics, we have chosen to normalize each one by dividing it with the maximum attained value, and then use their convex combination in the final objective function. The maximum values are acquired from the parasitic impedance cost maps (Figure 3.1), and robustness maps (Figure 3.4). Hence, the convex combination of normalized objectives for our multi-criteria optimization is

$$J = w C_n + (1 - w)(-\rho_n) \quad (3.8)$$

where C_n and ρ_n are the normalized values of parasitic impedance cost and robustness margin, respectively, and $w \in [0, 1]$ represents the weighting. Note that, the cost function, J , minimizes $-\rho_n$ which is equivalent to maximizing ρ_n . Each value of the weighting parameter, w , gives a different problem realization for the multi-criteria optimization, and the resulting set of optimal solutions for all realizations yield the Pareto front. Weighting parameter $w \in [0, 1]$, equally spaced by 0.001 increments, is used to construct the Pareto front curve.

3.4.1 Design Selection

Figure 3.5 shows the Pareto front curve for integration order, $\alpha = 1$, which reflects the tradeoff between the objectives. The maximum robustness margin is achieved when the parasitic impedance cost is at its maximum value, resulting in a poor transparency performance. On the contrary, the parasitic impedance cost function attains its minimum, yielding to the highest transparency, when the robustness margin is at its minimum, leading to the worst stability robustness. Even though one can study the tradeoff using the Pareto front, the final design requires selecting an optimal solution on the Pareto front curve.

An optimal solution is selected from the Pareto front curve in three steps. Using the pHRI scenarios studied in this dissertation (Section 3.2.3.2), we explain and illustrate by examples how to 1) consider possible limitations on the optimization objectives (i.e. transparency and stability robustness objectives), 2) impose secondary design criteria, and 3) complete the design selection by choosing an optimal solution on the Pareto front curve.

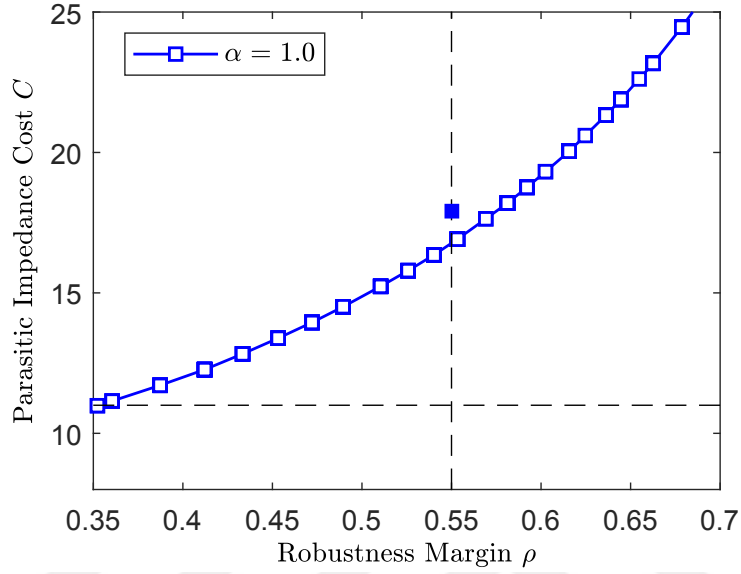


Figure 3.5: Pareto front curve (consisting of non-dominated, i.e. truly optimal, solutions denoted by empty squares) for IOAC ($\alpha = 1$) obtained by multi-criteria optimization, and an exemplary dominated (i.e. sub-optimal) solution (denoted by filled square) obtained by sequential optimization (where $\rho = 0.55$ is used as a constraint prior to optimization). The horizontal dashed-line denotes an exemplary upper bound for parasitic impedance cost of $C = 11$. The vertical dashed-line represents the robustness margin of $\rho = 0.55$.

3.4.1.1 Limitations on the Optimization Objectives

The subtle aim of the presented framework is to provide a broad perspective on the controller design problem. This is achieved by selecting cost functions (for this study, stability robustness and transparency) for the optimization problem and then computing optimal solutions for all costs. However, different tasks may demand specific limitations on these objectives. For this reason, we will focus on our pHRI scenario given in Section 3.2.3.2 to solidify such task specific limitations.

Let's assume that there is an upper bound on the parasitic impedance cost for a specific pHRI task (see the horizontal dashed-line in Figure 3.5 for $C = 11$). Inspecting this line and Pareto front curve suggests that a robustness margin of $\rho = 0.35$ can be achieved under the

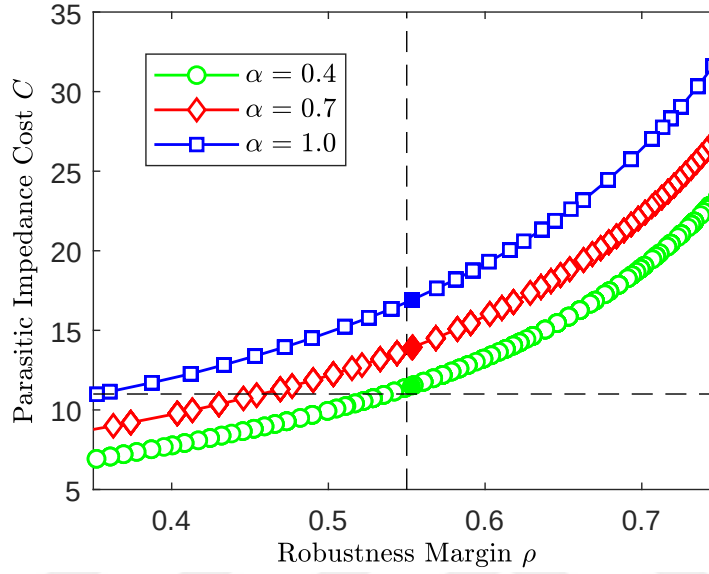


Figure 3.6: Pareto front curves for IOAC ($\alpha = 1$), FOAC ($\alpha = 0.7$ and 0.4). The horizontal dashed-line denotes an exemplary upper bound for parasitic impedance cost of $C = 11$. The vertical dashed-line represents the robustness margin of $\rho = 0.55$. The solutions represented by filled markers are the selected optimal solutions, tabulated in Table 3.2.

given constraint on the parasitic impedance cost. On the other hand, for another pHRI task, robustness margin could be more critical than parasitic impedance if the environment and/or human arm impedance is prone to significant change. For example, inspecting Figure 3.4 reveals that any controller parameter set having robustness margin of $\rho = 0.55$ maintains the robust stability up to $k_{eq} = 1610$ N/m, which is also the highest stiffness allowable in our third exemplary scenario given in Section 3.2.3.2 (see the vertical dashed-line in Figure 3.5 for $\rho = 0.55$). Therefore, all the optimal solutions leading to $\rho < 0.55$ is eliminated from any further consideration. Same elimination is also conducted for the optimal solutions on Pareto front curves of other integration orders presented in Figure 3.6. When both criteria are considered ($C \leq 11$, $\rho \geq 0.55$), there is no optimal solution for IOAC while there are optimal solutions for FOAC ($\alpha = 0.4$, $\alpha = 0.7$).

3.4.1.2 Imposing Other Design Criteria

After identifying the task specific limitations and imposing them on the Pareto front, the designer is free to choose any of the remaining optimal solutions for each integration order, noting that any solution on the Pareto front is a non-dominated, i.e. optimal, solution. On the other hand, there may be some other design criteria in which the designer may want to impose but have not been considered during the optimization. For such a case, the Pareto methods not only allow the other design criteria to be considered for the decision but also let the designer adjust these criteria while monitoring their effect on the set of non-dominated solutions [Unal et al., 2008].

For the case study given in this dissertation, it is assumed that the stability robustness and the transparency are the optimization objectives. However, once an understanding of the trade-off between the optimization objectives is achieved thoroughly, the designer is free to introduce new criteria to narrow down the set of optimal solutions further. For the pHRI task used in this study, we introduce an additional criterion, requiring the cut-off frequency of the closed-loop system to be larger than the bandwidth of the human arm's intended movements.

3.4.1.2.1 Cut-off Frequency of the Closed-Loop System: It is well known that intended movements of human arm is band-limited [Brooks, 1990]. When human physically interacts with a system, it is desired that the cut-off frequency of the system should be larger than that bandwidth. During the execution of a pHRI task, human physically interacts with a robot and environment whose reflected impedance is characterized by $Z_{\text{disp}}(s) = F_h(s)/V(s)$, as described in Equation (2.11) for our system. To study the cut-off frequency of this closed-loop system, the transfer function $T_{\text{disp}}(s) = X(s)/F_h(s)$ is calculated using the reflected impedance. The cut-off frequency, ω_c , of the closed-loop system is investigated for the remaining solutions on the Pareto front after imposing the task specific limitations.

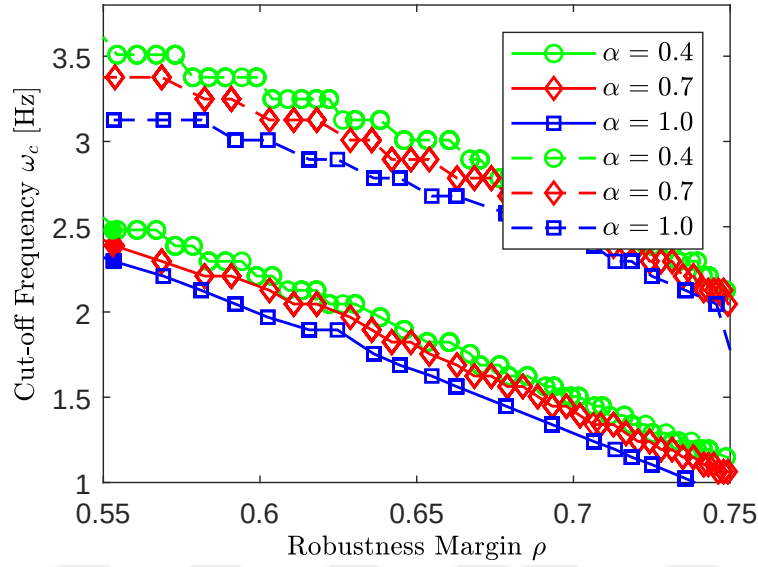


Figure 3.7: The cut-off frequency, ω_c , of $T_{\text{disp}}(s)$ as a function of ρ for the optimal solutions leading to $\rho \geq 0.55$. Solid and dashed lines are for $k_e = 610$ and $k_e = 1010$ N/m, respectively. The solutions represented by filled markers are the selected optimal solutions, tabulated in Table 3.2.

3.4.1.3 Deciding on an Optimal Controller

Figure 3.7 shows the cut-off frequencies, ω_c , of the remaining optimal solutions on the Pareto front for our pHRI system. As $k_e = 610$ N/m is the lower bound of the environment stiffness for the third pHRI scenario given in Section 3.2.3.2, ω_c under this stiffness value were considered for each set of optimal solutions, noting that, increase in the environment stiffness, k_e , increases ω_c (Figure 3.7). Since the bandwidth of the intended movements of human arm is around 2 Hz [Brooks, 1990; Dimeas and Aspragathos, 2016], the solutions leading to $\omega_c < 2.3$ Hz (a tolerance of 15% was considered on ω_c) were also eliminated from any further consideration. Thus, an optimal solution that satisfies $\omega_c \geq 2.3$ was selected as the final design for each integration order (see Table 3.1). We observe that FOAC ($\alpha = 0.4, \alpha = 0.7$) is a better choice than IOAC ($\alpha = 1$) since FOAC results in higher ρ and lower C , leading to more robust and transparent design (see Table 3.1).

Table 3.1: Parameters, stability robustness, and the parasitic impedance cost of the optimal controllers for the third pHRI scenario given in Section 3.2.3.2 where $\omega_c \geq 2.3$ Hz and $\rho \geq 0.55$ are desired.

α	m_F [kgs $^{\alpha-1}$]	b_F [Ns/m]	ρ	C	w
1	3.2	90	0.553	16.9	0.796
0.7	6.0	74	0.568	14.5	0.755
0.4	16.7	56	0.594	13.0	0.737

Table 3.2: Parameters and the parasitic impedance cost of the optimal controllers for the third pHRI scenario given in Section 3.2.3.2 where $\rho = 0.553$ is chosen which is the robustness margin for $\alpha = 1$ (see Table 3.1).

α	m_F [kgs $^{\alpha-1}$]	b_F [Ns/m]	C	w
1	3.2	90	16.9	0.796
0.7	5.8	71	13.9	0.770
0.4	15.4	49	11.5	0.776

As the main objective of the case study is to compare the tradeoff between stability robustness and transparency, we can make an alternative design selection for FOAC to result in the same robustness margin as IOAC (see Table 3.2). Note that, FOAC leads to higher transparency than IOAC when both controllers are designed to ensure the same robustness margin. The controllers tabulated in Table 3.2 were implemented for the pHRI experiments and a thorough comparison is reported in Section 3.5.

For comparison, a design utilizing the sequential optimization was also made. For sequential optimization, we chose $\rho = 0.55$ as a constraint (since this is sufficient to ensure stability for $k_{eq} \leq 1610$ N/m) and optimized the parasitic impedance cost for maximum transparency considering this constraint under IOAC. We would like to express that the

solution obtained by such sequential optimization is sub-optimal as it is already dominated by the Pareto front under IOAC (see Figure 3.5), noting that the parasitic impedance cost is lower under the solutions obtained by the Pareto optimization (see Table 3.2).

An important advantage of Pareto methods is that designer only needs to decide on an optimal solution and the tradeoff between objectives after obtaining the Pareto front. The weighting parameter, w , for each exemplary design is given in Tables 3.1 and 3.2. A designer may not prefer to construct entire Pareto front, but wishes to optimize the controller parameters for minimizing the J in Equation (3.8) under the w values given in Tables 3.1 and 3.2 only. However, please note that values of the weighting parameter, w , for each design is different and these values cannot be easily determined by intuition alone. A thorough knowledge on the tradeoff characteristics is needed before deciding on the values of w , which is not available a priori.

3.4.2 Comparison of Interaction Controllers

Using Pareto optimization approach not only allows the designer to make an informed decision by studying the tradeoff for interaction controllers, but also enables fair comparisons among various interaction controllers having different structures and/or physical interpretations.

A close inspection of the Pareto front reveals a significant result: The Pareto front curve for the IOAC is completely dominated by those of the FOACs (see Figure 3.6). In other words, parasitic impedance cost under IOAC is always larger than those of FOACs for the same robustness margin, therefore, FOAC allows a better compromise between the stability robustness and transparency. Furthermore, it can be easily seen that the Pareto front curve for integration order $\alpha = 0.4$ is superior to the others considered in this study. Hence, the best compromise between stability robustness and transparency is obtained under $\alpha = 0.4$ among the controllers considered in this study.

Note that for interaction controllers having different forms or types than the ones considered in this study, Pareto front curves do not necessarily dominate each other, that is, some could be superior to others for a specific range of robustness margin objective while

inferior to the others for another range. In general, Pareto methods do not suggest that one structure is always superior to other, but show which structure is better for which range of objectives. Consequently, it can be stressed out that the Pareto front curves provide an objective comparison tool for interaction controllers of different forms and types since they allow the designer to study, inspect, and compare all optimal controllers and tradeoffs simultaneously.

3.4.3 Verification of the Optimal Controllers

All three controllers tabulated in Table 3.2 (note that the corresponding pHRI scenario is also the one considered in our experimental pHRI study reported in Section 3.5) were designed to have the same stability robustness. Hence, here, we only validate the transparency by inspecting the parasitic impedance under these controllers, while the robustness characteristics were examined during our pHRI experiments, reported in Section 3.5.

To verify the parasitic impedance characteristics of the controllers tabulated in Table 3.2, a simple experiment was performed with the robotic arm. It is clear that using the inverse of Equation (3.1), the velocity response of the robot can be found to a given interaction force. Considering this, a chirp signal varying in frequency from 0.01 to 5 Hz (logarithmically spaced) and having an amplitude of 1 N was applied to the robot as an interaction force. The robot's velocity response (i.e. velocity of the end-effector) was recorded. Fast Fourier transform (FFT) was applied to the recorded velocity and the input force signal, and the transfer function was calculated in the frequency domain to estimate the parasitic impedance of the robot experimentally (see Figure 3.8 for the magnitude of estimated parasitic impedance functions). As expected, among the optimized controllers tabulated in Table 3.2, FOAC ($\alpha = 0.4$) allows the highest transparency since the magnitude of parasitic impedance under this controller was the lowest.

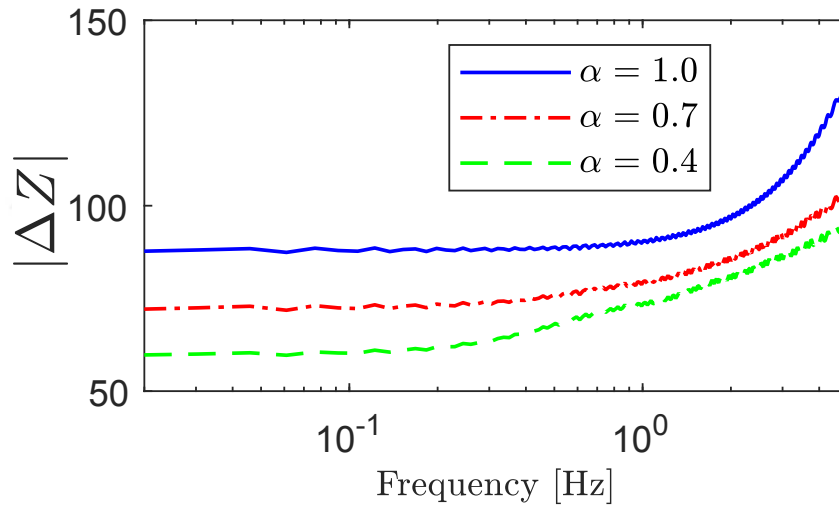


Figure 3.8: Magnitude of the parasitic impedance, acquired experimentally, as a function of frequency for the controllers tabulated in Table 3.2.

3.5 A Controlled pHRI Experiment: Continuous Contact with Environment

In pHRI, maximizing transparency, while maintaining robust stability is desired. Our stability robustness and transparency analyses show that FOAC offers a better tradeoff between these objectives than IOAC. Specifically, FOAC allows higher transparency than that of IOAC for the same level of robustness margin. This feature of FOAC can improve human performance in pHRI tasks involving especially contact interactions with environment where the human desires to feel the environment impedance alone.

A controlled human subject experiment was designed to further investigate the tradeoff between stability robustness and transparency under the controllers whose parameters are tabulated in Table 3.2. The task involved contact interactions with a nonlinear environment formed by two linear springs.

3.5.1 Experimental Procedure

In our experimental setup, human operator manipulates the robot to interact with an environment where its stiffness is varied based on the depth of compression (see Figure 3.9). This is achieved using two different springs (spring 1 and spring 2 in Figure 3.9a). Spring 1 ($k_1 = 610$ N/m) is connected between a fixed support and the end-effector of UR5 robot, as shown in Figure 3.9a. Spring 2 ($k_2 = 400$ N/m) becomes active when the depth of compression is more than 45 mm. Hence, the environment stiffness may change abruptly from $k_e = 610$ to $k_e = 1010$ N/m during the interaction. The subject grasps the handle to guide the end-effector and compresses the springs. The springs simply represent a layered environment in which the robot guided by a human operator is in continuous contact, as in drilling a wall or inserting a needle into soft tissue. In the experiments, the subjects are asked to compress the springs up to a depth of 55 mm, (ramp phase, Figure 3.9b), and then, hold it at that position for 5 seconds (hold phase, Figure 3.9c). In order to make the compression rate equal for each subject, a visual cursor (i.e. the blue rectangle, labeled as "C" in Figure 3.9b) moving with a constant speed ($v_c = 2$ cm/s) is displayed on the computer screen. The other details of the experimental procedure is the same as the one reported in Section 3.5.1.

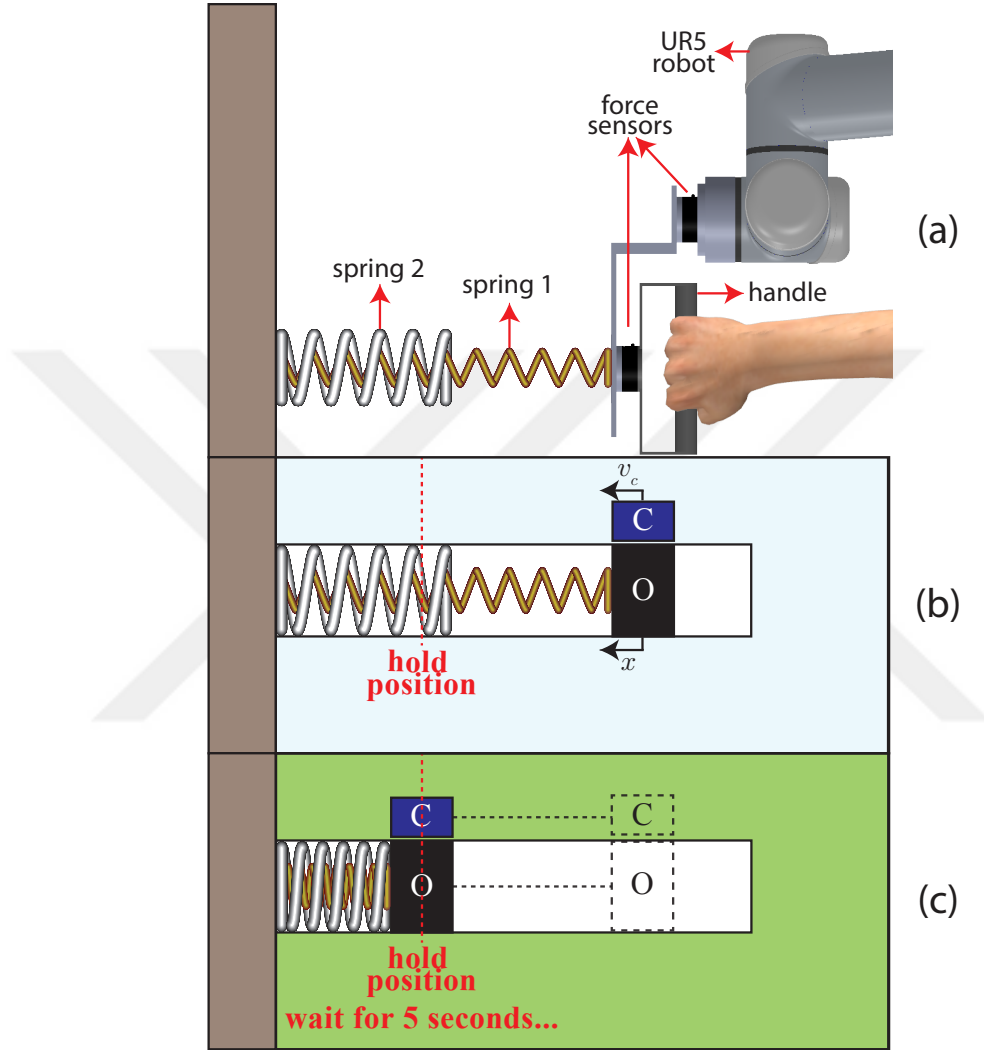


Figure 3.9: The experimental setup (a), and visual feedback (b,c) displayed to the subjects during the experiments.

We compared subjects' performance for the controllers tabulated in Table 3.2. Hence, three different controllers, IOAC ($\alpha = 1$), FOAC ($\alpha = 0.7$), and FOAC ($\alpha = 0.4$) were tested in this experiment. The task was repeated 10 times for each controller. Thus, there were 30 (3×10) trials in the experiment, which were displayed to the subjects in random order, while the order was same for each subject. Prior to the actual experiment, each subject was given a training session of 15 (3×5) trials to get her/him familiar with the setup. 10 subjects (5 males and 5 females, average age = 29 ± 6) participated in this experiment. The subjects gave informed consent about their participation in the experiment. The ex-

perimental study was approved by the Ethical Committee for Human Participants of Koc University.

3.5.2 Data Collection and Performance Metrics

During the experiment, the robot constrains the motion of the subjects along a horizontal line while they compress the springs. The force F_h applied by subject is the sum of the forces required for compressing the springs (F_e) and generating the motion trajectory of the robot (i.e. interaction force F_{int}); $F_h = F_e + F_{\text{int}}$, where $F_e = k_e \Delta x$ (Δx is the amount of compression) is not influenced by the controller. F_{int} is the interaction force measured by a force sensor (Mini40, ATI Inc.), filtered, and fed back to the admittance controller. The force applied by subject F_h (measured by a second sensor, Mini40, ATI Inc.) and the interaction force F_{int} are linearly dependent on each other since F_e depends on the amount of compression only, and is independent of viscous and inertial effects coming from the controller and the robot. As the portion of force applied by subject to overcome the parasitic impedance of the robot is the interaction force, by inspecting this force alone, we can compare the transparency performance for each admittance controller.

We use average interaction force ($F_{\text{int}}^{\text{ave}} = 1/(t_e - t_b) \int_{t_b}^{t_e} |F_{\text{int}}(t)| dt$) to quantify the interaction performance under different controllers, and average force applied by human subjects ($F_h^{\text{ave}} = 1/(t_e - t_b) \int_{t_b}^{t_e} |F_h(t)| dt$) to investigate the human effort, where, t_b and t_e are the beginning and ending times of a phase (ramp or hold), respectively. We also inspect the energy consumed to overcome the parasitic impedance of the robot ($E_{\text{int}}(t) = \int_{t_i}^t F_{\text{int}}(t)v(t)dt$) as a function of time t , and then use it for estimating the total energy consumption ($E_{\text{int}}^{\text{tot}} = E_{\text{int}}(t_f)$), where t_i and t_f are the beginning and ending times of a trial. Moreover, the total work done by the human ($W_h = \int_{t_i}^{t_f} F_h(t)v(t)dt$) is also investigated. In addition, peak amplitude of oscillations in interaction force $A_{F_{\text{int}}}$, force applied by human A_{F_h} , and end-effector position A_P are computed using FFT analysis as measures to compare the robustness under each controller.

3.5.3 Data Analysis

For each subject, the performance metrics $E_{\text{int}}^{\text{tot}}$ and W_h were calculated for the entire duration, $F_{\text{int}}^{\text{ave}}$ and F_h^{ave} were computed for the ramp phase, $A_{F_{\text{int}}}$, A_{F_h} , and A_P were evaluated for the hold phase of all trials and then the mean values were normalized for the analysis (Figures 3.10, 3.11, and 3.12). We performed one-way ANOVA to investigate the statistical significance of these results. In all statistical analyses, a significance level of $p = 0.005$ was used to test the null hypothesis.

3.5.4 Results

Figures 3.10a, 3.10b, and 3.10c show average peak amplitude of oscillations in force applied by the subjects A_{F_h} , interaction force $A_{F_{\text{int}}}$, and end-effector position A_P during the hold phase, respectively. Although these values were slightly lower under FOAC, the differences were not significant.

Figures 3.11a and 3.11b illustrate the average energy consumed to overcome the parasitic impedance of the robot $E_{\text{int}}^{\text{tot}}$, and the work done by the subjects W_h , respectively. We observed a statistically significant effect of controller on $E_{\text{int}}^{\text{tot}}$. Specifically, it was significantly lower under FOAC than that of IOAC. Moreover, it was the lowest under FOAC ($\alpha = 0.4$). In addition, FOAC also reduced the work done by the subjects slightly.

Average interaction force $F_{\text{int}}^{\text{ave}}$, and force applied by the subjects F_h^{ave} during the ramp phase were depicted in Figures 3.12a and 3.12b, respectively. We observed a statistically significant effect of controller on $F_{\text{int}}^{\text{ave}}$. Specifically, $F_{\text{int}}^{\text{ave}}$ was significantly lower under FOAC than that of IOAC. Moreover, $F_{\text{int}}^{\text{ave}}$ was the lowest under FOAC ($\alpha = 0.4$).

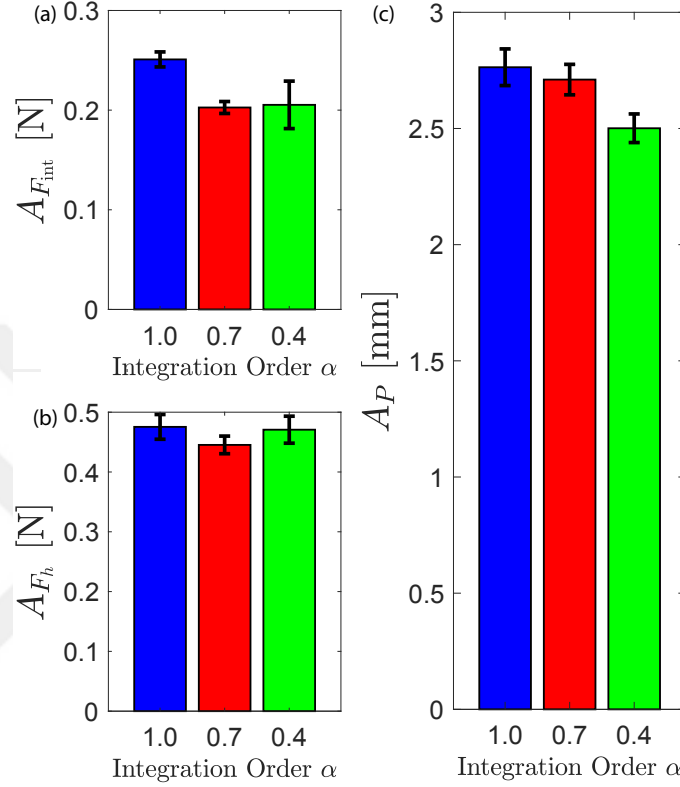


Figure 3.10: The means and the standard errors of means of normalized performance metrics; peak amplitude of oscillations in (a) force applied by the subjects, A_{F_h} , (b) interaction force, $A_{F_{int}}$, and (c) end-effector position, A_P , during the hold phase.

3.5.5 Discussion of the Experimental Results

We compared the performance of FOAC with that of IOAC for a pHRI task involving contact interactions with an environment whose stiffness changes as a function of compression depth to imitate the behaviour of a nonlinear and layered structure. A set of optimal admittance controllers at the same level of stability robustness were tested in our experiment, and their transparency performances were compared.

None of the subjects experienced any instability while interacting with the robot during the experiments. Note that robust stability was especially needed during the hold phase as the highest equivalent stiffness was expected during this phase. The fact that no instability was observed provides evidence that each controller provided sufficient stability robustness.

In order to compare the energy dissipation characteristics of these controllers, the am-

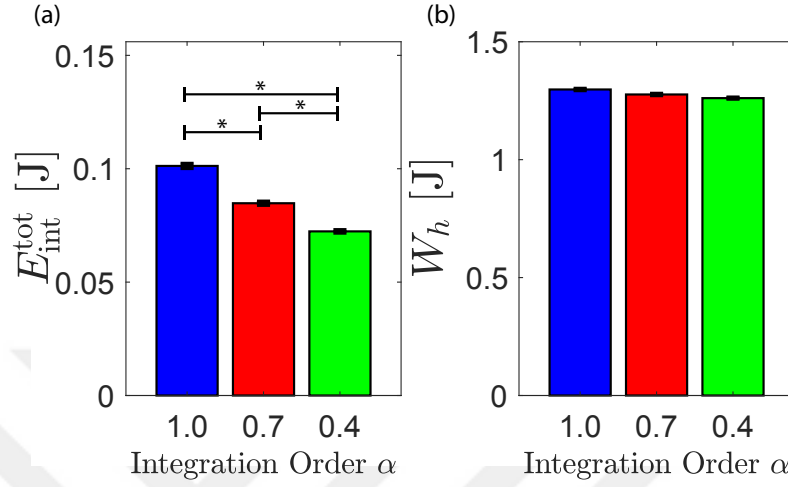


Figure 3.11: The means and the standard errors of means of normalized performance metrics; (a) average energy consumed to overcome the parasitic impedance of the robot, $E_{\text{int}}^{\text{tot}}$, and (b) the work done by the subjects, W_h (Horizontal bars with * on top indicate statistical significance between the results of the two corresponding controllers).

plitude of oscillations in force applied by the subjects, A_{F_h} , interaction force $A_{F_{\text{int}}}$, and end-effector position of the robot, A_P , were used. We did not expect a significant difference between these values during the hold phase (Figure 3.10), where the equivalent stiffness is the highest. Since each controller was designed to maintain the robust stability up to $k_{\text{eq}} = 1610$ N/m, their energy dissipation capacities should be similar.

We expected that the energy consumed to overcome the parasitic impedance of the robotic system during the ramp phase would be significantly lower under FOAC for $\alpha = 0.4$ as it was found to yield the lowest parasitic impedance cost in our computational analysis (Table 3.2). Indeed, it was lower under FOAC in our experimental study (Figures 3.11a and 3.13). Furthermore, average interaction force during the ramp phase was reduced as integration order was lowered (Figure 3.12a). The fact that both the energy consumption and the force to overcome the parasitic impedance were lower under FOAC revealed that higher transparency was achieved. On the other hand, the difference between IOAC and FOAC in terms of the average force applied (Figure 3.12b) and the work done by the subjects (Figure 3.11b) was not significant during the ramp phase since compressing the

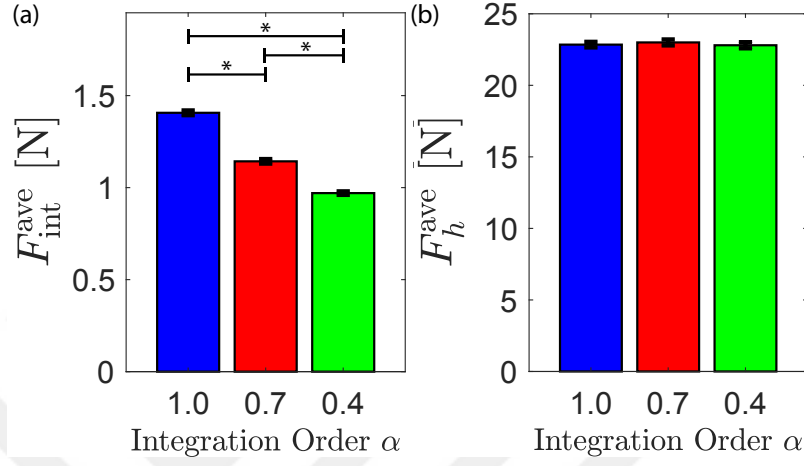


Figure 3.12: The means and the standard errors of means of normalized performance metrics; (a) average interaction force, $F_{\text{int}}^{\text{ave}}$, and (b) force applied by the subjects, F_h^{ave} , during the ramp phase (Horizontal bars with * on top indicate statistical significance between the results of the two corresponding controllers).

springs required a significant portion of the total energy consumed by the subjects during the task.

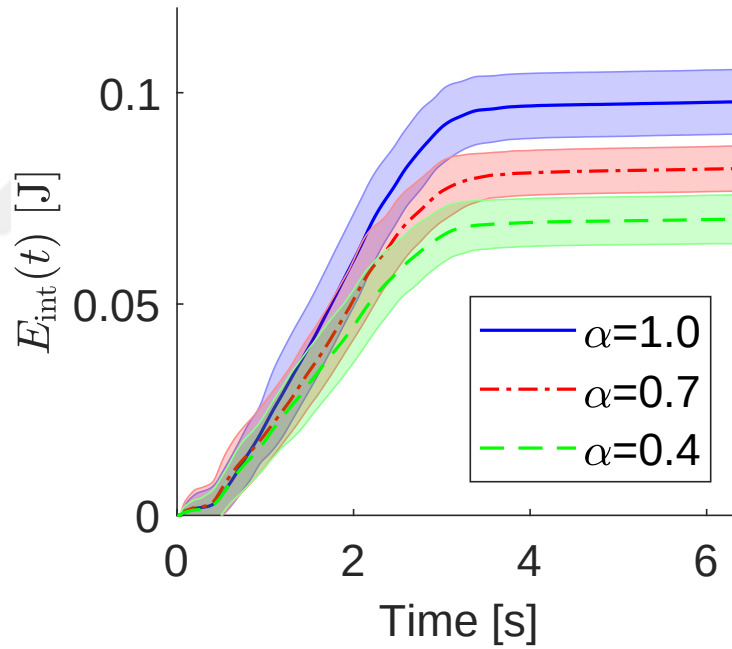


Figure 3.13: Energy consumed to overcome the parasitic impedance of the robot as a function of time, $E_{\text{int}}(t)$.

Chapter 4

CONCLUSIONS

In the first part of this dissertation, we proposed and introduced a new controller, fractional order admittance controller (FOAC), for pHRI systems. FOAC introduces an extra controller parameter, the integration order, that helps regulate the dynamics of the interaction between human and the robot, bringing more flexibility to the controller design. FOAC is advantageous as it enables effective control of the frequency dependent response, while still relying on the powerful analysis tools provided by linear systems theory. For instance, FOAC allows for effective damping to increase with frequency, providing further robustness at relatively high frequencies, while not significantly interfering with the quality of the interaction at low frequencies where intentional control takes place.

In the second part of this dissertation, given the fact that controller affects the coupled system dynamics in a non-trivial manner, rendering analytical design methods infeasible, we proposed a general computational approach for optimal design of interaction controller. In our approach, the controller parameters are optimized for maximum attainable transparency and stability robustness.

Our computational approach resembles to the complementary stability analysis by Buerger and Hogan [2007]. Their method relies on prioritization of one objective over another, leading to sub-optimal solutions (see Figure 3.5), while our approach is based on Pareto optimization that allows the designer to make an informed decision by studying all possible sets of optimal solutions on the Pareto front.

Furthermore, when the coupled system is destabilized due to an unforeseen change in the environment and/or human arm dynamics, selecting a new design on the Pareto front curve allows alternative optimal controllers, and informs the designer about their degree of stability (i.e. robustness) without a need for rerun of any analysis.

As our design framework allows optimizing the controller parameters for the best trade-off performance, it allows for interaction controllers with different structures to be compared. Furthermore, this comparison can be made for all possible optimal designs for these controllers. Pareto optimization approach allows the designer to study, inspect, and compare tradeoff between objectives simultaneously, therefore, Pareto front curves can be used as objective comparison tools for interaction controllers having different physical interpretations.

We demonstrated the practical implementation of our approach for the design of integer and fractional order admittance controllers. As discussed in Chapter 2, a fair comparison between FOAC and IOAC is particularly difficult, since the control parameters for each integration order have different physical characteristics and units [Aydin et al., 2018]. Thanks to Pareto front curves, an objective comparison between these controllers was achieved. Analyzing the Pareto front curves suggested that the curve for IOAC is inferior to that of FOAC. Hence, FOAC allowed a better compromise between stability robustness and transparency. Moreover, for the case of FOAC, the best integration order that minimized the parasitic impedance of the robot and maximized the transparency of the pHRI system was determined among the integration orders considered in this study. We also verified the computational design by experimental evidence coming from a pHRI study that involves contact interactions with a nonlinear environment.

In this dissertation, time-variant behavior of human arm was neglected in the controller design process and analyses. Similarly, adaptive controllers were not considered in this work in order to use powerful analysis tools of LTI systems. Time varying nature of human/environment and adaptive controllers will be the focus of our future research work.

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