# Towards Robots as Teammates:

## Human-Robot Collaboration Models for Temporal Coordination in Human-Robot Teams

Thesis submitted in partial fulfillment

of the requirements for the degree of

"Doctor of Philosophy"

by

Someshwar Roy

Submitted to the Senate of Ben-Gurion University of the Negev

September 2016
Beer-Sheva

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Approved by the advisors: Prof. Yael Edan _____

Prof. Joachim Meyer _____

Approved by the Dean of the Kreitman School of Advanced Graduate Studies _____

September 2016
Beer-Sheva

This work was carried out under the supervision of

Prof. Yael Edan

Prof. Joachim Meyer

In the

Department of Industrial Engineering and Management

Faculty of Engineering Sciences

**Research-Student's Affidavit when Submitting the Doctoral Thesis for Judgment**

I, Someshwar Roy, whose signature appears below, hereby declare that:

✓ I have written this Thesis by myself, except for the help and guidance offered by my Thesis Advisors and collaborator Dr. Yoav Kerner.

✓ The scientific materials included in this Thesis are products of my own research, culled from the period during which I was a research fellow.

Date: 25/09/2016 Student's name: Someshwar Roy Signature:

*A year spent in artificial intelligence is enough to make one believe in God.*

— Alan Perlis

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*"The single greatest cause of happiness is gratitude"*

- *Auliq-Ice*

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# Abstract

This dissertation deals with the development and investigation of different aspects of temporal coordination among collaborating partners – human and robot – working in a team sharing work- and time-space for a collaborative handover task.

## Methodology

### *Overview*

The overall approach includes two main steps. First, human-human joint-action in collaborative handover tasks was investigated through field studies, simulations and experiments to understand its design implication for developing Human-Robot (H-R) collaborative systems. Based on this study, the second step included the development of three human-robot collaboration models – *Timing, Sensor and Adaptive* – for H-R team-work. The performance of these three models was evaluated using analytical, simulation and experimental analyses. The influencing parameters of a H-R collaborative system investigated in this research can be categorized into collaboration design-, task- and agent-intrinsic parameters.

### *Analyses*

Analytical and simulation studies were done for users with *different proficiency levels (novice/expert)*. Analytical study of adaptive systems also included the study of the effect of *prolonged work-periods (learning/fatigue)*. Using experimental analyses, the performance of the H-R system in each of the three models was evaluated for three task types with varying length and complexity – *Short & Simple, Long & Simple, Long & Complex*. The study helped in understanding the strengths and limitations of each of the collaboration models and their specific suitability for different task types.

### *Measures of H-R collaborative system performance*

i. **Objective Measures:** Coordination in the team is measured in terms of temporal fluency using the following metrics – total idle time, total assembly time (human and robot together) and rate of successful handover.

ii. **Subjective Measures:** Questionnaires were used in two of the four experimental studies for subjective assessment of the system and the team-coordination in the collaborative handover task.

## Investigating Human-Human joint-action

Human-human joint-action in collaborative handover tasks was investigated for a case-study of hand-over of bottles in a supermarket. It included a three pronged approach – work-methods field studies in multiple supermarkets, simulation analysis using Jack, an ergonomics software package, and by conducting an in-house lab experiment on human-human joint-action by re-creating the environment and conditions of a supermarket. The developed methodology provides a systematic method to analyze similar tasks.

Evaluations included both objective and subjective measures. Objective analyses revealed, among other things, that (a) the task of the giver is physically more strenuous than that of the receiver, (b) the art of well-coordination among the team partners is not influenced by the increasing or decreasing frequency of handovers. Subjective evaluations revealed, among other things, differences in the way individual team partners perceive a common joint-action depending upon their role (giver/receiver). Results also indicate the crucial role of temporal perception and prediction in the success of collaborative handover tasks. Combining the results of the three analyses, this research provided a basis for the development of the H-R collaboration models.

## Study of H-R collaborative system

The main influencing parameters of H-R collaboration were identified and broadly classified into collaboration design-, task- and agent-intrinsic parameters. The current study of the H-R collaborative system focuses on the problem of a H-R team in a handover task (the task) requiring temporal coordination among the collaborating teammates when the external influencing parameters in the process are user-proficiency (an agent-intrinsic parameter), task length and complexity (task parameter), in a repetitive collaborative task (task parameter), for a single agent non-buffered interaction (collaboration design parameters), for different coordination protocols (collaboration design parameter), when there is learning/fatigue in the process (an agent-intrinsic parameter).

### *Human-Robot collaboration models*

Based on the basic principles of how humans perceive and process time, three Human-Robot collaboration models – *Timing, Sensor and Adaptive* – were developed for H-R team-work in a handover task.

i. **Timing Control Model** – Coordination is based on the principle of single or multi-level rhythmic interaction. The operational cycle of robot actions is only governed by time.

ii. **Sensor Control Model** – The robot actions are initiated by a triggering signal from a sensor that provides information about the human's state of action. The signal helps the robot to compute the probable time of the subsequent handover, and hence it may plan its action accordingly.

iii. **Adaptive Model** – The robot perceives, predicts and adapts in time to the rhythm of the human action, based on a temporal model. The system does a time-series analysis of the past and incoming temporal data to anticipate the time of the next handover cycle.

### Analytical and simulation study of H-R collaboration models

The behavior of the H-R collaborative system in each of the three collaboration models was studied and compared using analytical and simulation analyses for users with different proficiency levels (novice/expert), prolonged work periods (learning/fatigue) and system reliability (the various factors that affect sensor data accuracy and mechanical constraints).

The analytical analyses were done by developing an objective function of the H-R system. The system objective function was developed by taking into account the costs of human waiting and robot idle time in each work cycle. To illustrate the methodology, three case-studies were presented for which exact solutions were found for the given context.

A simulation model of the H-R system was developed in Matlab. Four case-studies were presented using the developed simulation model to study the effect of system recalibration, different coordination protocols and human-factors (novice/expert) on team coordination and productivity. The collaborative scenarios investigated in the case-studies were simulated for $10^6$ times using the Monte Carlo method.

The analytical and simulation study of the H-R collaborative systems resulted in the development of coordination strategies and guidelines for better team-coordination in a collaborative handover task and improved system productivity in a team-work, which are presented separately in *Chapter 8*.

### Experimental study of H-R Collaboration models

Using experimental analyses, the performance of the H-R system in each of the three collaboration models was evaluated for three types of tasks with varying degree of complexity in terms of cognitive- and time-demand – *Short & Simple, Long & Simple, Long & Complex.*

An integrated human-robot collaborative work-cell was designed for the experiments. This work-cell facilitated close Human-Robot interaction in a shared work-, time-space collaborating with the aim of executing a time-critical task. Three experiments with 200 subjects in total were conducted to validate, evaluate and compare the models.

Statistical analyses included total idle time, total assembly time and rate of successful handovers for each of the collaboration models. The study helped to understand the strengths and limitations of each of the collaboration models and their specific suitability for different tasks type. Among others, results indicate that while the *Timing Control Model* is best suited for short and simple tasks, the *Adaptive Model* is best suited for long and simple, and long and complex tasks. The experiments also demonstrated the importance of time- perception in H-R collaborative system.

### Guidelines for designing H-R collaborative system

Based on the study of Human-Human joint action together with the analytical, simulation and experimental study of H-R team work in collaborative handover tasks, system design implications and guidelines for designing robots as co-workers in collaborative tasks were recommended *(detailed in Chapter 8).*

## Keywords

Human-Robot team-work, fluency, temporal coordination, team coordination, joint-action, collaborative task

This dissertation is in part based on the following publications:

**Journal Papers**

D.1 **Someshwar R.**, Edan Y. (2017) "Investigating joint-action in short-cycle repetitive handover tasks: the role of Giver Versus Receiver", International Journal of Social Robotics (IJSR). [Impact Factor – 2.5, Computer Science – Q1] DOI 10.1007/s12369-017-0424-9 (in press).

**Peer-reviewed conference proceedings**

D.2 Peretz Y., Sayfeld L, **Someshwar R**., Edan Y. (2015) "Evaluation of Human-Robot Collaboration Models for Fluent Operations in Industrial Tasks", Robotics Science and Systems (RSS), Workshop on Human-Robot Hand-Overs.

http://how.sciencesconf.org/68784

D.3 **Someshwar R.**, Kerner Y. (2013) "Optimization of Waiting Time in Human-Robot Collaboration", IEEE International Conference on Systems, Man & Cybernetics (SMC).

http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=6722083

D.4 **Someshwar R.**, Kerner Y. (2013) "Analyzing Co-operative Human-Robot System as an Optimization Problem", Israeli Conference on Robotics (ICR), Tel Aviv.

http://www.ariel.ac.il/sites/shiller/icr2013/Program_ICR2013.pdf

D.5 **Someshwar R.**, Meyer J., Edan Y. (2012) "A Timing Control Model for Human-Robot Synchronization", IFAC Proceedings Volumes, 45(22): 698-703.

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D.6 **Someshwar R.**, Meyer J., Edan Y. (2012) "Models and Methods for Human-Robot Synchronization", IFAC Proceedings Volumes, 45(6): 829-834.

http://www.sciencedirect.com/science/article/pii/S1474667016332529

D.7 **Someshwar R.**, Gontar V. (2012) "An Adaptive Human-Robot Synchronization Model: Towards Developing "Conscious Robots", 5th International Conference on Cognitive Systems (CogSys), Austria.

http://cogsys2012.acin.tuwien.ac.at/doc/cogsys2012_proceedings/109Someshwar_Roy.pdf

**Journal papers under review**

D.8 **Someshwar R**, Kerner Y, Meyer J, Edan Y. "Towards Robots as Teammates: Analytical and Simulation Study of Control Models for Team Coordination in Human-Robot Collaborative Manufacturing", Mechatronics [Under Review] [Impact Factor – 2.4, Computer Science Applications – Q1]

**Journal papers in preparation**

D.9 Sayfeld L., Peretz Y., **Someshwar R**., Edan Y. "User-Experience in Human-Robot Collaboration: Performance Evaluation of Different Populations in Collaborative Task".

# Chapter 1 | Introduction

***Chapter Overview***

A global overview of the problem investigated in this dissertation is presented. Four specific research objectives dealing with the problem of temporal coordination in Human-Robot collaborative system for handover tasks are subsequently presented. This is followed by a section explaining the research significance, which explains how this dissertation provides a comprehensive view on the design needs and requirements for developing an H-R system. The chapter concludes by highlighting the specific research contributions and innovations of the current study.

## 1.1. Description of the problem

Robots are still primarily kept and operated in safety cages and separated from human operators (Stanescu et al. 2008). To widen the contributions of robotics, the current trend in industrial automation is to enable human-robot collaboration (Nikolaidis et al. 2013; Sadrfaridpour et al. 2014; Cherubini et al. 2016).

Recent advances in industrial robots that showcase this upcoming trend are Baxter Robot (Fitzgerald 2013), ABB Yumi and Kuka IIWA-LBR Light Weight Robot (Bischoff et al. 2010). These are smart, flexible, and easily customizable robots suitable for diverse tasks, involving close human-robot collaboration, sharing both work- and time-space (Kamali et al. 1982; Parasuraman et al. 2000; Fitzgerald 2013). These collaborative robots and the vision to integrate them in our workplace as partners, co-workers and peers provides many promises for advanced systems if the challenges that come along with it can be overcome (Haddadin et al. 2011).

One of the key challenges in these collaborative systems is coordination among the partners (Glasauer et al. 2010; Cakmak et al. 2011). Human-Robot collaboration is often structured in a stop-and-go rigid regime of turn-taking operations inducing delays (Hoffman and Breazeal 2010). For robots to become social or human-like in collaborative actions, robot-human interactions must reach a level of fluency, close to that of human-human interactions (Hoffman and Breazeal 2007).

There has been a growing interest in the robotics research community in understanding the role of timing and temporal coordination in Human-Robot Interaction (HRI) (Glasauer

et al. 2010; Hoffman 2013; Iqbal et al. 2014; Maniadakis and Trahanias 2014; Lorenz et al. 2015). Research focused on different aspects, such as timing from the perspective of joint-action in teams (Huber et al. 2008; Glasauer et al. 2010), temporal cognition in artificial systems (Maniadakis and Trahanias 2011; Maniadakis and Trahanias 2014), and methods to improve communication and interactive features in robots e.g., (Michalowski and Sabanovic 2007; Namera et al. 2008; Iqbal et al. 2014; Grand et al. 2014).

Several studies on temporal aspects of human-robot collaboration have used timing as a measure of temporal fluency among the collaborating agents and as a performance measure of the overall H-R system (Hoffman and Breazeal 2007; Shah et al. 2009; Wilcox et al. 2012; Hoffman 2013; Mutlu et al. 2013; Nikolaidis et al. 2013; Gombolay et al. 2013b; Huang et al. 2015).

This dissertation investigates the problem of integrating a human and a robot in a collaborative handover task. The research focus is on temporal coordination in a human-robot team, using temporal fluency as a measure, with the external influencing parameters involved are user-proficiency (an agent-intrinsic parameter), task length and complexity (task parameter), in a repetitive collaborative task (task parameter), for a single agent non-buffered interaction (collaboration design parameters), for different coordination protocols (collaboration design parameter) when there is learning/fatigue in the process (an agent-intrinsic parameter).

## 1.2. Research objectives

The main objective of this research is to investigate the temporal aspects of human-robot collaboration when working as a team in handover tasks. The specific research objectives are to:

1. Investigate Human-Human joint-actions in handover tasks and their design implications for developing H-R collaborative systems for handover tasks.
2. Investigate coordination strategies for better H-R team-coordination and improved system productivity in handover tasks.
3. Develop Human-Robot collaboration models of time perception for fluent and intuitive team-coordination in handover tasks.

Based on this research, system design implications for improving the temporal coordination in a Human-Robot team for handover tasks will be developed.

## 1.3. Research significance

1. The study of human-human joint-action shows how the given job-role (giver/receiver) determines user-perception and behavior in a collaborative task. The results of this study have several design implications for developing H-R collaborative systems for repetitive handover tasks. These tasks are commonly found in supermarkets, warehouses and manufacturing industries. The results are therefore relevant for the robotics community.

2. The developed H-R collaboration models provide ways for integrating a human and a robot in a work-cell sharing time- and work-space. It has several practical applications in industries with the need for automating low-volume, complex and customized processes which are still done by human labor.

3. Human-Robot collaboration is currently structured in a stop-and-go rigid regime of turn-taking operation inducing delays. The developed models can improve the temporal coordination of a H-R system. This can make the collaboration process fluent and natural, and hence, offer a better user-experience.

4. The study of H-R collaborative system shows the dependence of the models and coordination strategies on several influencing parameters, including task length and complexity, coordination protocols, user-proficiency and work-periods.

5. The combined studies on human-human joint-actions and H-R collaborative systems provide a comprehensive view of the design needs and requirements for developing an H-R system with fluent and intuitive team-coordination in handover tasks.

## 1.4. Research contributions and innovations

1. The study of human-human joint-action in repetitive handover tasks showed the conflicting perspective of the team-partners – a giver and a receiver. It provides insight on how a joint-action is perceived differently by a giver and a receiver, and hence how different their needs and behavior are in a handover task.

2. Three H-R collaboration models were developed, based on how humans perceive and process temporal events in a collaborative task, as studied in the research on

human-human joint action. The models improve the temporal coordination between the partners and the productivity of an H-R system.

3. The three-pronged design analysis methodology presented here – simulation, analytical and experimental – can be used by the robotics community to compare and evaluate the performance of H-R collaborative systems.
4. The influence of user-proficiency, learning/fatigue and task-type on the design requirements of an H-R system shows that different H-R collaboration models can be the best model of collaboration, depending on the needs and requirements of the scenario.
5. Coordination strategies for fluent Human-Robot handovers in a team-work are proposed.

# Chapter 2 | Scientific Background

***Chapter Overview***

A brief literature review of the investigated problem is presented. The first section deals with human-robot collaborative manufacturing and recent trends in industrial robotics. System performance metrics of Human-Robot collaborative systems and the role of human-factors in the design of such systems are subsequently presented to give an overview of the design challenges. The next two sections deal with joint-action in repetitive handover tasks, with presentations of the psychology and robotics literature concerning temporal coordination in human-human and human-robot collaboration. The review ends with an overview of the different approaches, tools and methods for analytical and simulation studies of human-robot system.

## 2.1. Human-Robot collaborative manufacturing

The current trend in industrial robotics is to expand the application of industrial robots beyond the safety cages by developing human-robot collaborative systems (Krüger et al. 2009; Tan et al. 2009; Duan and Tan 2011; Duan et al. 2012; Unhelkar et al. 2014). This requires the development of smart, flexible and customizable robots that share work and time-space (Fitzgerald 2013). Such robot assistants can be used as multi-purpose robots in collaboration with human workers for diverse tasks in industries, e.g., in the packaging of products with different shapes, sizes and weights or in assisting in the assembly of complicated objects (Cherubini et al. 2016; Tsarouchi et al. 2016a) or in aircraft assembly industries (Gombolay 2013; Gombolay et al. 2013b). Several robotic developments are advancing this approach, including Baxter Robotics (Fitzgerald 2013), ABB Yumi and Kuka IIWA-LBR Light Weight Robot (Bischoff et al. 2010).

### 2.1.1. Human-Robot system performance

Human-Robot (H-R) collaborative systems may result in improved efficiency and accuracy (Kamali et al. 1982; Parasuraman et al. 2000) since they rope in the individual strengths of humans (e.g., perception, adaptivity, decision making) and robots (e.g., speed, accuracy, consistency). H-R system performance has been measured using different methods, including operator workload and team performance (Howard 2005; Howard 2007), human physiological responses (Sarkar 2002) or by determining the autonomy level based on cost-

benefit decision analyses (Bechar et al. 2009; Tkach et al. 2011). H-R system performance can also be measured in terms of task metrics (Nikolaidis et al. 2015) and fluency metrics (Hoffman 2013). Temporal fluency is defined as the level of coordination among the collaborating partners and measured using three common metrics (Hoffman and Breazeal 2007; Shah et al. 2009; Wilcox et al. 2012; Gombolay et al. 2013a; Hoffman 2013) – concurrent time, human idle time, functional delay and the robot idle time.

This dissertation employed temporal fluency as H-R system performance metric in a three-pronged design analysis framework, consisting of simulation, analytical and experimental study of H-R system. This framework can be used by the robotics community to compare and evaluate the performance of H-R collaborative systems.

### 2.1.2. Human-factors in Human-Robot collaborative system

Humans obviously play an important role in H-R collaborative systems, so human factors must be considered (Casper and Murphy 2003). A human-aware robot can significantly improve team-coordination in collaborative tasks (Lasota and Shah 2015). Robot-human hand-overs can be made seamless by taking human preferences into account (Cakmak et al. 2011; Strabala et al. 2013). Anticipation of timing in human-human collaboration (also known as joint-action) is influenced by several intrinsic system variables, including perceptual latency (Seifried et al. 2010), temporal preparation (Bausenhart et al. 2010), and rhythm of operation (Fraenkel 1994; Sanabria et al. 2011). Besides, it can also be influenced by external factors (e.g., experience, fatigue, training) that affect intra- and interpersonal movements to become temporally coupled (also known as entrainment) (Vesper et al. 2011), which in turn induces synchronization.

In a human-robot repetitive handover task, waiting times arise if the human or the robot are early or late at the point of handover (Strabala et al. 2013). The waiting times of the collaborating partners have been defined as human waiting time and robot idle time (Hoffman and Breazeal 2010) in repetitive handover tasks. Waiting times result in irregular handover patterns, generating a lack of coordination in the H-R system (Hoffman 2013), which directly affects the overall system productivity.

This dissertation investigated the influence of human-factors on team fluency in a H-R collaborative system. Several human-factors including user-proficiency, user-state (learning/fatigue), coordination protocols, task-complexity, length of the task and the

frequency of H-R interaction during a task were investigated in this study. The study helped to understand the strengths and limitations of each of the H-R collaboration models and their specific suitability for different types of tasks from a user-centric design perspective.

## 2.2. Joint-action in repetitive tasks

There are many examples of short-cycle and repetitive joint-actions among humans, such as drill sessions, military parades and professional rowing. Literature in human-factors define short-cycle repetitive task as a physical task, done by a human with an individual cycle length of the task / sub-task varying approximately between 2 sec (or less) to a maximum of 20 sec (Moore and Wells 2005; Garg et al. 2006; Bosch et al. 2012). Examples of such tasks, as stated above, which are done in a team are related to joint-action. It is defined in (Sebanz et al. 2006) as "joint action can be regarded as any form of social interaction whereby two or more individuals coordinate their actions in space and time to bring about a change in the environment". It may seem that joint-action in synchrony is the domain of professionals and experts, however, knowingly or unknowingly (Richardson et al. 2007), every human coordinates his/her actions with others in many tasks, such as in aerobic classes, basketball or while doing the dishes with a partner.

The science of joint-action is discussed in cognitive psychology (Vesper et al. 2011; Vesper et al. 2013), philosophy (Bratman 1992) and musicology (Keller 2008; Merker et al. 2009). Recently, this field has received much attention in the HRI community (Mörtl et al. 2012; Clodic et al. 2014; Mörtl et al. 2014). It has profound importance for designing friendlier and ergonomic Human-Robot (H-R) collaborative systems. Such design methodologies and principles have been successfully implemented in a number of cases (Huber et al. 2008; Lorenz et al. 2011; Boucher et al. 2012; Mutlu et al. 2013; Strabala et al. 2013). The worldwide popularity of the toy robot Keepon (Kozima et al. 2008) is a simple example of designing human-friendly robots by taking cues from Human-Human rhythmic interaction.

Investigation in goal-directed joint-tasks (Lorenz et al. 2011) (such as two people moving a table together) show that humans tend to synchronize their arm movements, which calls for precise movements. In general, movement synchronization is a guiding dynamical process that leads to stable coordination patterns in natural human-human joint action (Mörtl et al. 2012). Hence, synchronization among the team partner must exist to be

able to work together. This helps in building team coordination, which plays an important role in joint-action in repetitive tasks.

The fluency (Hoffman 2013) of team coordination among humans engaged in a joint-task depends on many factors, including, team communication (Eccles and Tenenbaum 2004; Richardson et al. 2005), agreeableness among team members (Neuman and Wright 1999; Bernardin et al. 2000), habit persistence for their preferences (Thunholm 2004) and their ability to adapt, attend and anticipate (Keller and Koch 2008). Adding to that, a joint-action in a short-cycle repetitive task involves closer and more frequent interaction. Therefore, for the robot and the human to collaborate successfully in such a H-R system, it has to be attuned to the actions of the human (Garg et al. 2006; Wilcox et al. 2012).

This dissertation presents a three-fold systematic approach to study and analyze joint-action in repetitive tasks. It also gives insight into the science of joint-action for short-cycle repetitive tasks and its implications for human-robot collaborative system design.

### 2.2.1 Human-Human and Human-Robot Handovers

A joint-action may involve direct or indirect handover between the collaborating partners. Studies in human-human handover, e.g., (Basili et al. 2009; Huber et al. 2013; Strabala et al. 2013; Moon et al. 2014; Huang et al. 2015) have been instrumental in designing robots with human like handovers, e.g., (Gharbi et al. 2015; Huang et al. 2015; Zheng et al. 2015). These human-human and human-robot handovers generally deal with face-to-face handover scenarios where communication between partners is possible through eye-gaze and other non-verbal communication cues (Gharbi et al. 2015). In such cases, the point-of-handover (p-o-h) in a joint-action is generally determined by the giver (Basili et al. 2009). In short-cycle repetitive handovers, however, there may or may not exist an eye-gaze in every handover cycle. In the absence of an eye-gaze by the receiver, a-priori expectation of the receiver about the probable p-o-h plays a more significant role in the success of the handover (Huber et al. 2013).

This dissertation showed the conflicting perspective of the team-partners – a giver and a receiver – in human-human joint-action in repetitive handover tasks. It provides insight on how a joint-action is perceived differently by a giver and a receiver, and hence how different their needs and behavior are in a handover task. Three H-R collaboration models were designed for H-R handover based on the study on human-human handover.

## 2.3. Temporal coordination

### 2.3.1. Temporal coordination in human-human collaboration

Humans' ability to perceive time is what makes them so good in coordination in collaborative tasks (Sebanz and Knoblich 2009). Some collaborative tasks like competitive rowing or hand clapping games require rhythmic interaction among the team partners requiring the ability to perceive rhythms (Keyfitz and McNeill 1996). Another type of collaborative tasks, like musical jam sessions or classical dance, require temporally adaptive interaction, which in turn requires the ability to perceive, predict and adapt according to the changing rhythms and/or incoming temporal cues (Merker et al. 2009). In the case of unstructured and complex collaborative tasks where prediction may not always be possible, humans rely on external stimuli, temporal or otherwise (Suri and Schultz 2001).

### 2.3.2. Temporal coordination in human-robot collaboration

The role of timing is often overlooked in the study of Human-Robot Interaction (HRI), let alone the study of Human-Robot Collaboration (HRC). Human-robot collaboration is often structured in a stop-and-go rigid regime of turn-taking operations inducing delays (Hoffman and Breazeal 2007). For robots to become social or humanlike in collaborative actions, robot-human interactions must reach a level of fluency close to that of human-human interactions (Hoffman and Breazeal 2010).

This requires action coordination, which is defined as the harmonization between the actions of a human and a robot, providing real-time coordination between them (Lorenz et al. 2015). Without such action coordination, the joint-efficiency of the collaborative system can be extremely poor (Huang et al. 2015). Joint-efficiency in this research is defined as the net throughput of the H-R system (i.e., the team work) for the given task (as opposed to their individual throughput or efficiency). Thus, system performance of such H-R systems is evaluated by considering both the human and the robot as integral contributors to performance (Oren et al. 2012).

There has been a growing interest in the robotics research community in understanding the role of timing and temporal coordination in HRI (Glasauer et al. 2010; Hoffman 2013; Iqbal et al. 2014; Maniadakis and Trahanias 2014; Lorenz et al. 2015). Research focuses on different aspects, such as timing from the perspective of joint-action in teams (Huber et al.

2008; Glasauer et al. 2010), on temporal cognition in artificial systems (Maniadakis and Trahanias 2011; Maniadakis and Trahanias 2014), and methods to improve communication and interactive features in robots e.g., (Michalowski and Sabanovic 2007; Namera et al. 2008; Iqbal et al. 2014; Grand et al. 2014).

Several studies focus on temporal aspects of human-robot collaboration. They deal with timing as a measure of temporal fluency among the collaborating agents and as a performance measure of the overall H-R system (Hoffman and Breazeal 2007; Shah et al. 2009; Wilcox et al. 2012; Gombolay et al. 2013; Hoffman 2013; Mutlu et al. 2013; Nikolaidis et al. 2013; Huang et al. 2015). These studies, however, do not consider the role of human-factors on temporal coordination and temporal perception of the partner that come into play in a collaborative teamwork.

The three H-R collaboration models developed and evaluated in this dissertation are based on the three principles of temporal coordination in human-human collaboration. Timing-based model is based on the principle of rhythmic interaction, Sensor-based model is based on external stimuli and Adaptive model is based on the principle of perceive, predict and adapt. These models improve the temporal coordination between the partners and the productivity of an H-R system. The influence of human-factors including, user-proficiency, user-state (learning/fatigue), coordination protocols, task-complexity and length on the design requirements of an H-R system shows that different H-R collaboration models can be the best model of collaboration, depending on the needs and requirements of the scenario.

## 2.4. Analytical and simulation study of human-robot coordination in a repetitive collaborative task

Analytical models of repetitive work cycles show the temporal behavior of a worker over time (Eilon 1964; Gentzler et al. 1977). Experimental studies on temporal behaviors of humans in repetitive tasks have also been done in the field of human factors and ergonomics (Garg et al. 2006; Dempsey et al. 2010; Bosch et al. 2012). These studies investigated temporal changes in humans' movement strategy over time and the influence of pace and temporal organization on human performance during a fatiguing short-cycle repetitive task. The studies provide design guidelines for better system ergonomics and higher productivity in repetitive tasks, done solely by humans. In contrast to these studies,

the research presented here investigates the collaborative performance of repetitive handover tasks by a human-robot system. So far, no system design guidelines on effective coordination strategies exist for such a task. The existing body of work on H-R system design guidelines generally deals with safety (Michalos et al. 2015; Zanchettin et al. 2016), and workstation layout problems (Tsarouchi et al. 2016b).

The analysis of an H-R system in an industrial context apparently makes the problem similar to workstation design and optimization issues – an area well investigated using analytical and simulation analyses. Examples of such analyses include the application of methodologies like Factorial Experiments (FE) and Response Surface Methodology (RSM), together with graphical simulation tools to find optimal solutions for multiple-objective workstation problems with multiple performance measures (Ben-Gal and Bukchin 2002). In ergonomic analyses, workstation design problems are generally investigated with the use of Digital Human Modeling and Simulation (DHMS) tools, e.g., (del Rio Vilas et al. 2012; Harari et al. 2017).

Investigation of these design issues as an integrated collaborative system with the human-in-the-loop has only lately received attention. Examples include the simulation model of an industrial H-R collaborative system (Ore et al. 2013; Khalid et al. 2015), and work-method studies of farmers for agricultural automation (Riemer and Bechar 2016), where the biomechanical workload and operation time of a human is analysed to find optimal H-R collaborative system design solutions. Simulation tools have also been employed for optimized task distribution in an H-R collaborative assembly task (Ding et al. 2014). Recent work also includes the use of interactive virtual environments as tools to model industrial H-R system (Matsas et al. 2016). H-R system modeling using analytical methods is useful for quantitative evaluations. Examples include (Nikolaidis et al. 2013), where the entropy rate of the Markov chain were computed to evaluate the system and (Someshwar and Kerner 2013), where operations research methods were used in optimizing the waiting times of the collaborating partners.

Analytical modelling of workstation design, flexible manufacturing system and its productivity optimization, focusing on scheduling and flexibility under different constraints, parameters and scenarios is another well investigated area (Akturk et al. 2005; Wilhelm and Zhu 2009; Al-Hinai and Elmekkawy 2011; Arviv et al. 2015). Scheduling problems of industries with temporal constraints (Levner et al. 1997; Agnetis 2000; Guo et

al. 2011) are of interest to the current research. However, previous investigations on analytical modelling excluded humans from the system control loop and focused on the optimization models. Recently temporal scheduling techniques were applied to the design of human-in-the-loop collaborative systems (Wilcox et al. 2012; Gombolay et al. 2013b). These scheduling techniques aim at decreasing the waiting/idle time of the partners to improve the system fluency (Hoffman 2013).

The analytical framework developed by Wang (Wang et al. 2015) shows the influence of the control scheme and scheduling strategies on H-R mutual trust and hence on the collaborating system design. Using the numerical simulation analysis in Matlab, they have shown how inclusion of human factors like H-R trust dynamics in scheduling strategies can improve H-R collaboration (Sadrfaridpour et al. 2014; Wang et al. 2015). This is an example that shows how analytical and simulation studies can be used to study H-R systems to understand the interaction of system parameters in different scenarios.

Other studies of analytical models of H-R collaborative systems deal with the kinematics and robust control framework (Krüger and Surdilovic 2008). The control scheme of an H-R system could be manual, semi-autonomous or autonomous, depending on the level of automation (LOA) of the system (Parasuraman et al. 2000). Together with the control schemes and LOA, a coordination protocol is needed between the partners for realizing the handover or the actual physical interaction. The coordination protocol can be defined as the pre-defined and explicit rules of collaboration or "high-level protocol used in coordination process" between the partners in a mutually dependent task (Kuwabara et al. 1995).

Effective H-R coordination strategies and their design implications have been presented for human-robot handover tasks (Huang et al. 2015) and for target recognition tasks (Tkach et al. 2011; Oren et al. 2012). (Huang et al. 2015) showed that different strategies, such as the 'slowing-down strategy' and the 'waiting strategy' can improve the team-coordination and offer better user-experience in a human-robot handover task.

This dissertation investigates team fluency and productivity of the H-R system using analytical and simulation analyses methods and proposes effective H-R coordination strategies. The methodology presented can be used to: *(i)* predict the level of team-coordination between the partners and hence performance of human-robot collaboration as a team; *(ii)* study the behavior of the system when the influencing parameters are tuned

thereby predicting the preferable (and when possible optimal) way to collaborate for dynamic scenarios; *(iii)* develop a system objective function which can be employed as a general design tool to measure H-R system performance.

# Chapter 3 | Methodology

***Chapter Overview***

The general problem definition investigated in this thesis and the overall approach are presented followed by the methodology of the sequential steps applied in this research. The steps include the investigation on Human-Human joint action, followed by the development of H-R collaboration models. Then, the influencing parameters of H-R collaboration and the measures of H-R system performance that were investigated are explained. The chapter concludes with the H-R system design analysis and evaluation methodology that was implemented to study, compare and evaluate the three H-R collaboration models.

## 3.1. General

### 3.1.1. Problem definition

An H-R collaborative task where the human and the robot physically collaborate with each other requires the accurate anticipation of the spatial and temporal point of handover for an efficient coordination during the process. *This research deals with the analysis of the timing component of this handover to improve team-coordination*.

### 3.1.2. The overall approach

The overall approach is described in Figure 3.1 and includes two main steps. Human-human joint-action in repetitive handover tasks was investigated to understand its design implication for developing H-R collaborative systems. The study included a three pronged approach – a field-study, simulation and experimental studies – for a case-study of short-cycle repetitive tasks, which includes the hand-over of bottles in a supermarket.

Based on this study, three human-robot collaboration models were developed – *Timing, Sensor and Adaptive*. The performance of these three models was evaluated using analytical and simulation analyses for users with different proficiency levels (novice/expert) and prolonged work periods. Using experimental analyses, the performance of the H-R system in each of the three models was evaluated for three types of handover tasks – short & simple, long & simple, long & complex. The study helped to understand the strengths and limitations of each of the collaboration models and their specific suitability for different handover task types.

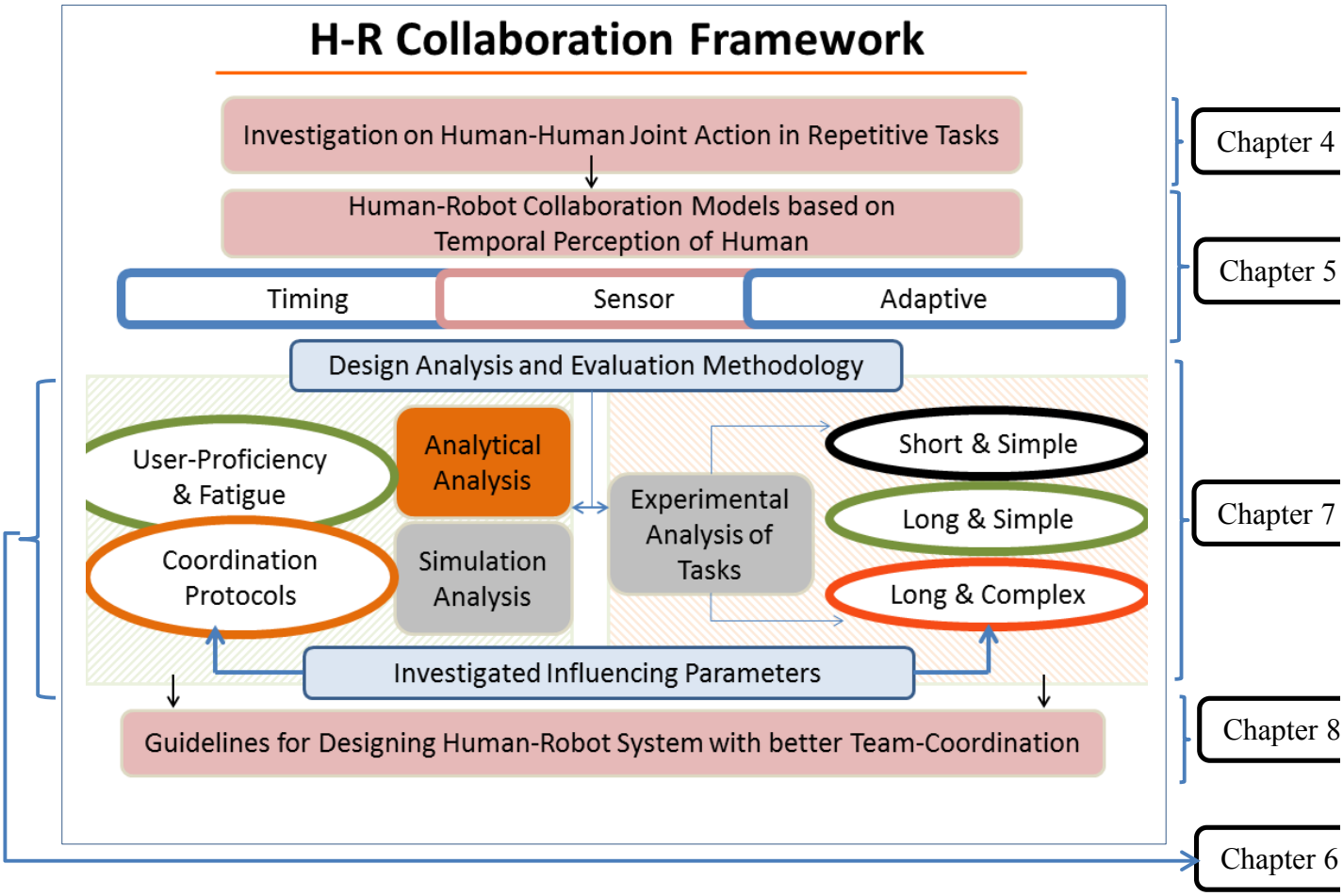



**Figure 3.1 An illustrative overview of the overall methodology employed in this research**

The study resulted in the development of coordination strategies for fluent and intuitive Human-Robot collaboration in handover tasks. The different studies on Human-Human joint-action and the H-R System for different user-proficiency, coordination protocols and task-types provide a holistic view on the design needs and requirements for developing a H-R system with fluent and intuitive team-coordination in handover tasks. The thesis concludes by presenting this in the form of design guidelines for developing H-R collaborative systems for handover tasks.

## 3.2. Human-Human joint action in repetitive handover tasks

*Chapter 4 describes this study in detail*

The human-human joint action in short-cycle repetitive handover tasks was analyzed through a real world case-study. The specific joint-action was the handover of bottles in a supermarket. It was analyzed in a project conducted as part of this thesis (BGU final project report, Kozak and Zeev, 2015) using three methods – (a) field studies of work-methods in

supermarkets, (b) simulation analyses using Jack, an ergonomics software package, and (c) lab experiments simulating the conditions of a supermarket.

The motivation behind the work-methods field studies was to get a first-hand understanding of the scenario, the problem, the needs, and the nature of the task, and at the same time to study the work methods of humans working in teams in supermarkets. It was carried out by recording data in three supermarket stores at different locations in southern Israel, followed by data analyses.

The Jack simulation study was conducted to analyze the involved bio-mechanics and ergonomic aspects of short-cycle repetitive tasks. It provided an understanding of which of the sub-tasks is physically more strenuous and hence could be delegated to a robot, if a human-robot collaborative system is commissioned for the given job.

Based on the observations and the data collected in the field studies, a laboratory experiment was subsequently carried out by re-creating the conditions of a supermarket. The lab experiment aimed at providing psychological aspects in human-human joint action for the given task. The experiment included two variables – shelf height (Higher Shelf/Lower Shelf) and frequency of handover (Normal Mode/Competitive Mode). As a result, the experiment had four phases in total and each of the pairs of participants went through all the four conditions: (i) Normal Mode – Higher Shelf, (ii) Normal Mode – Lower Shelf, (iii) Competitive Mode – Lower Shelf, and (iv) Competitive Mode – Higher Shelf.

*Task-related performance* of participants was measured through an objective analysis of the number of bottles shelved every 10sec during each phase, and with the off-line video data analysis of the joint-task, focusing on the level of coordination in the team during the task. The level of coordination was assessed by measuring the partners' waiting time in every handover.

*Subjective analyses* of the participants' experiences in the experiment were assessed through two questionnaires, given during and after the experiment. Subjects were asked to report their experiences by comparing the current phase with the previous ones in terms of (i) comfort and (ii) coordination /synchronization during each of the intervals. At the end of the experiment, subjects were given a post-experimental questionnaire to assess the psychological aspects in human-human joint action in repetitive tasks.

All experiments were formally approved by the BGU Human Subject Research Ethics Committee.

## 3.3. Human-Robot collaboration models

*Chapter 5 describes this study in detail*

Three Human-Robot Collaboration Models – Timing, Sensor and Adaptive – were developed, based on the above study of human-human joint action in repetitive tasks. The models are based on the three preliminary ways in which human, knowingly or unknowingly (Richardson et al. 2005) processes the perceived time in order to coordinate effectively in a collaborative task.

**Timing Control Model** – It is based on the principle of single or multi-level rhythmic interaction. The operational cycle of robot actions is governed by only one parameter in this case, and that is time. The robot performs a series of pre-defined tasks at fixed intervals of time that are set by the end-user, depending upon the needs and operational demands of the scenario. An example where this model suits the scenario is a human assisting a pick and place robot in an assembly station.

**Sensor Control Model** - This collaboration model is based on the principle that in the case of unstructured and complex collaborative tasks, where prediction may not always be possible, humans rely on external stimuli, temporal or otherwise (Suri and Schultz 2001; Sebanz and Knoblich 2009).The robot actions are initiated by a triggering signal, issued as a function of the temporal or state information of the human's action. When receiving the signal, the robot computes the likely time of the subsequent handover and plans its action accordingly.

**Adaptive Control Model** - This model is inspired by the human's ability to perceive, predict and adapt according to the changing rhythms and/or incoming temporal cues (Merker et al. 2009; Vesper et al. 2011; Keller et al. 2014). They allow humans to adapt in time with each other, giving rise to what psychologists define as *emergent coordination.* In the temporally adaptive model, the robot perceives, predicts and adapts in time to the rhythm of the human action. *The perception, anticipation and adaptation are purely temporal in this model*. The system does a time-series analysis of the past and incoming temporal data to anticipate the time of the next handover cycle.

## 3.4. Influencing parameters investigated

The influence of the following types of parameters was investigated (Figure 3.2). It is explained in detail in *Chapter 5* (sec. 5.1).

a) **Collaboration design parameters**: Parameters that are connected to the design of the workspace and to the collaboration aspects fall into this category. For example, coordination protocol, buffered or non-buffered coordination.

b) **Task parameters**: Parameters that are connected to the design of the task fall into this category. For example, task length and complexity, exclusive task or shared task.

c) **Agent-intrinsic parameters**: The inherent characteristics of the participating agents (human and robot) in a collaborative task can be defined as agent-intrinsic parameters (Someshwar et al. 2012a). For example, learning or fatigue, system reliability, user-proficiency.

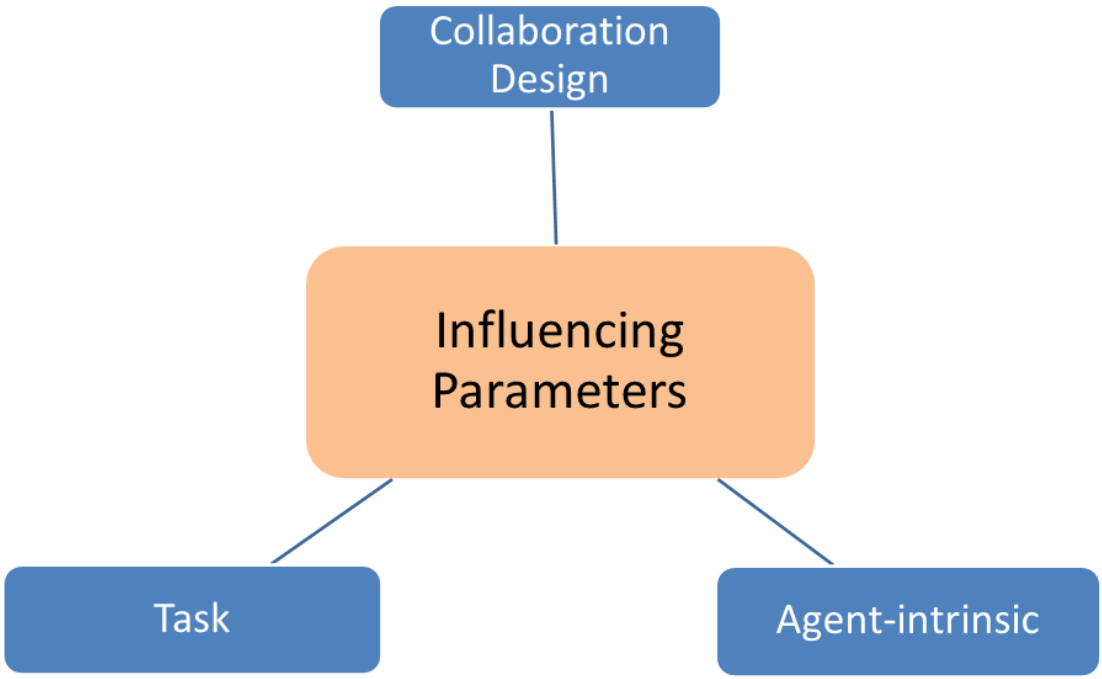



**Figure 3.2 Investigated influencing parameters of H-R collaboration**

## 3.5. Measures of H-R collaborative system performance

### 3.5.1. Objective measures

*Team Fluency* is measured in this research in terms of temporal coordination using the total idle time, total assembly time (human and robot together) and rate of successful handover as metrics (Hoffman and Breazeal 2007; Hoffman and Breazeal 2010; Hoffman 2013).

i. Total idle time – It is the sum of the total waiting times of the human for the robot or vice-versa at the point of handover in a team-work. Idle time generally arises when one of the team-partner is delayed, making the other wait for the handover.

ii. Total assembly time – It is the sum of the total time taken by the human and the robot together as a team to accomplish the given team-work.

iii. Rate of successful handovers – When the human and the robot arrive at the point of handover at almost the same time, and the H-R handover is executed with no waiting times, it is defined in this research as successful handovers. Rate of successful handover is thus calculated as,

$$Rate\ of\ successful\ handover\ = \frac{Nr.of\ successful\ handover}{Total\ nr.of\ handovers} \times 100$$

### 3.5.2. Subjective measures

Questionnaires were used in two of the four experimental analyses for subjective assessment of the system, the collaborative task and the participants' experience of working in different experimental conditions. They were analyzed using Microsoft Excel and the R software.

## 3.6. Analytical and simulation study of H-R system

*Chapter 6 describes this study in detail*

The behavior of the H-R collaborative system was studied using analytical and simulation analyses for different user-proficiency levels (novice/expert) and system reliability functions (the various factors that affect sensor data accuracy and mechanical constraints) for different pre-defined rules of collaboration (defined as coordination protocols) and control models. An objective function of the H-R system was developed for the analytical analyses taking into account the costs of human waiting and robot idle time in each work cycle. This objective function was used as the H-R system performance measure to

determine the level of coordination (temporal fluency) between the partners for a given scenario. To illustrate the methodology, three case-studies were developed and presented for which exact solutions were found for the given context. The results of the case-studies were further studied by looking into its design implications to get a holistic view for developing H-R collaborative systems for handover tasks.

Subsequently, complex collaborative scenarios were investigated to study the effect of techniques like system recalibration, different coordination protocols and influencing parameters like user-proficiency (novice/expert), system reliability (sensor data accuracy) on H-R team coordination in handover tasks. Analytical analyses of the effect of these factors together made the problem computationally intensive and complex by nature.

Therefore, a simulation model of the H-R system was developed in Matlab to explore the interaction of these factors and their effect on team coordination and system productivity. Four case-studies were analyzed using the developed simulation model. They show the effects of system recalibration, different coordination protocols and human-factors (novice/expert) on team coordination and productivity. Each of the collaborative scenarios was simulated for 1000x1000 times using the Monte Carlo method. The values of each of the variables (robot total time, RTT and human total time, HTT) were randomly sampled each time to analyze H-R system performance.

A comparative analysis of the results of the analytical and simulation study of the H-R system was done for one of the case-studies to assess the robustness of the two approaches. The analytical and simulation study of the H-R collaborative system resulted in the development of coordination strategies for fluent and intuitive human-robot handover in collaborative tasks.

## 3.7. Experimental study of the H-R system

*Chapter 7 describes the experimental study in detail (click on chapter 7)*

Using experimental analyses, the performance of the H-R system in each of the three models was evaluated for three types of tasks – short & simple, long & simple, and long & complex. It was conducted as part of two final projects performed as part of this thesis (BGU final project reports, Sayfeld and Peretz 2014, Moyal and Goldshtein, 2015).

An integrated human-robot collaborative work cell was designed for the experiments. The system consisted of a 5 DOF revolute robotic arm (Scorbot ER4U) mounted on a table

top with an area dedicated to human-robot interaction and two other areas dedicated to the primary and secondary (if applicable) tasks of the robot respectively. This work-cell facilitated close Human-Robot interaction in a shared work, time-space collaborating with the aim of executing a time-critical joint task (as done in the manufacturing and assembling industry).

Three experiments with 200 subjects in total were conducted to validate, evaluate and compare the models for three types of collaborative task, which vary in their degree of complexity in terms of cognitive- and time-demands. Statistical analyses were conducted on the total idle time, total assembly time and the rate of successful handovers for each of the collaboration models. The study helped to understand the strengths and limitations of each of the collaboration models and their specific suitability for different types of tasks.

# Chapter 4 | Investigating joint-action in repetitive handover tasks

***Chapter Overview***

Human-human joint-action in short-cycle repetitive tasks was investigated for a bottle handover task, using three methods – work-methods field studies, simulation analyses and an in-house lab experiment (BGU final project report, Kozak and Zeev 2015). Analyses included both objective and subjective measures. These three methods and their respective results are presented in detail in three dedicated sections, 4.2, 4.3 and 4.4. This is followed by a common discussion on the three methods along with comprehensive analyses. The chapter concludes with several guidelines for the design and development of user-friendly human-robot systems for joint-action in collaborative tasks.

## 4.1. Methods

The human-human joint action in short-cycle repetitive handover tasks was analyzed through a real world case-study (Kozak and Zeev 2015). The selection of a real world task is important for providing reliable and valid results. The scenario investigated represents a typical job of supermarket workers – the task of stacking bottles in store shelves from the cartons. The bottle handover task in supermarkets was analyzed using three methods – (a) work-methods field studies in supermarkets, (b) simulation analysis using Jack, an ergonomic software package, and (c) in-house lab experiments simulating the conditions of a supermarket.

The motivation behind the work-methods field studies was to get a first-hand understanding of the scenario, the problem, the needs, and the nature of the handover task, and at the same time, to study the work methods of humans working in teams in handover tasks in supermarkets. It was carried out by visiting three supermarket chains at different locations in Israel and recording data in real world conditions, followed by data analyses. Field studies indicated that this job is generally done by a team of two people, each with a specific role. One is a giver whose job is to pick up a bottle from the carton and hand it to the receiver whose job it is to take the bottle from the hands of the giver and place (and align) it at the right location on the shelf.

A Jack simulation study was conducted to analyze the involved bio-mechanics and ergonomic aspects of short-cycle repetitive tasks. It provided an understanding which of the

sub-tasks is physically more strenuous, and hence could be delegated to a robot, if a human-robot collaborative system is commissioned for the given job.

Finally, based on the observations and the data collected from the field-study, an in-house lab experiment was subsequently executed by re-creating the conditions of a supermarket. The lab experiment aimed at providing psychological aspects in human-human joint action for the given task.

All experiments were formally approved by BGU Human Subject Research Committee.

## 4.2. Work-methods field studies in supermarkets

Work-methods analyses were conducted at different supermarkets in southern Israel during the fall of 2014 (Figure 4.3 and Figure 4.4a). In most locations, video recording was not allowed by the store manager, and in these cases, the following objective data was manually recorded by two observers after notifying workers and receiving their consent: the cycle time of each handover, the number of missed or unsynchronized handovers, the difference in height between the given carton of bottles and the shelf, rest time and the total ON time. ON time in repetitive tasks is defined as the amount of time a team spends working together at a stretch (Dempsey et al. 2010). The two observers were assigned different responsibilities. One was solely responsible for noting the cycle times of each handover; the other was responsible for noting the number of missed or unsynchronized handovers and other objective measures, as mentioned above. Data was recorded separately for the higher, medium and lower shelves (Kozak and Zeev, 2015).

### 4.2.1. Results

The average cycle times varied between 1.7sec (SD = 0.5) and 3.3sec (SD = 1.4) (Table 4.1). The number of missed or unsynchronized handovers over a single ON time varies between 7 and 19%. The speed (cycle time) and efficiency of the team was found to depend upon the relative height between the given carton of bottles and the shelf, which defines the amount of relative bending required in the task. The shelves heights in the supermarket were 165 cm for the upper shelf, 124 cm for the medium shelf and 10 cm for the lower shelf.

**Table 4.1 Results of the work-methods field studies in supermarkets**

| S. Nr. | Shelf height (cm) | Bottle carton height (cm) | Average Cycle Time (sec) | Std. Deviation (sec) | % of Unsynchronized Handovers |
|---|---|---|---|---|---|
| 1 | 0 | 30 | 3.3 | 1.4 | 12.49 |
| 2 | 0 | 100 | 3.7 | 1 | 11.27 |
| 3 | 124 | 100 | 1.7 | 0.5 | 23.20 |
| 4 | 165 | 30 | 3.4 | 0.9 | 11.95 |
| 5 | 165 | 100 | 2.3 | 0.9 | 17.44 |

## 4.3. Software simulation

Jack (Siemens 2015) is an ergonomic simulation software package from Siemens, used for modeling humans in workplace environments, aimed to address the ergonomic aspects of manual operations. It is commonly used for testing and validating designs and operations for a wide variety of human factors, including injury risk, fatigue limits, time of operation, user-comfort, line-of-sight, energy expenditure and other important parameters (Siemens 2015). Two humans with equal physical features, a shelf and a stack of bottles were modeled in the simulation environment (Figure 4.1).

To simulate the conditions of a supermarket, the human models were given the task to stack bottles in the shelves – one was assigned with the role of a giver and the other as a receiver. Only one bottle was handed over at a time. The shelves in the simulation environment had the dimensions, 145 cm – upper shelf height, 95 cm – medium shelf height and 43 cm – lower shelf height. The height of the shelves (higher/medium/lower) and the physical attributes of the human model (Body-Mass Index) were varied and its influence on the fatigue measures was evaluated.

The analysis was done for three groups representing 5, 50 and 95 percentile of the population. This population distribution is an in-built feature of the simulation software and is based on the height-weight ratio of the entire world population. The fatigue measures included Lower Back Analysis (LBA), Estimated Recovery Time Needed, and Muscle Strain Time History.

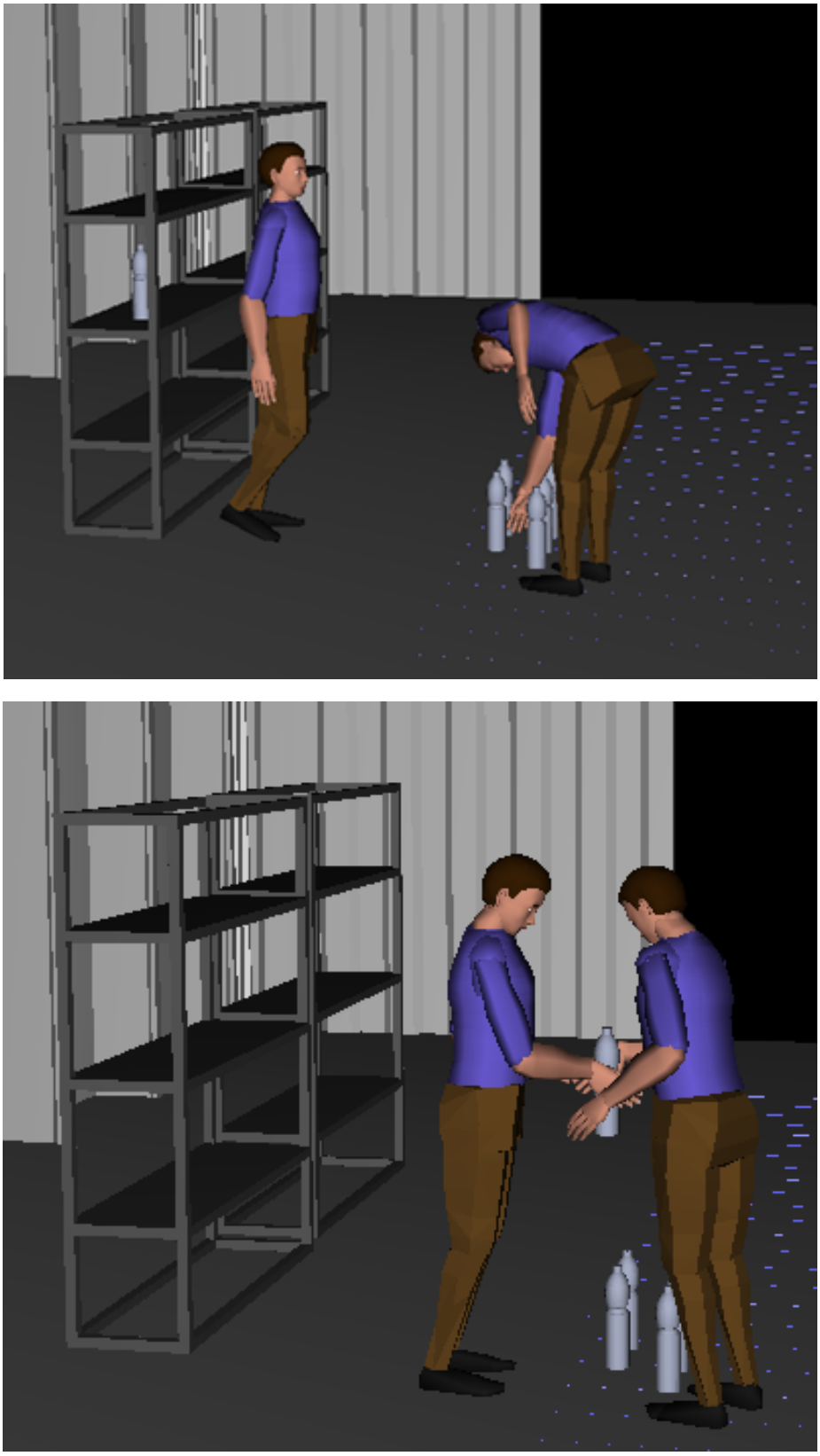


**Figure 4.1 Example of a bottle hand-over in the Jack simulation environment**

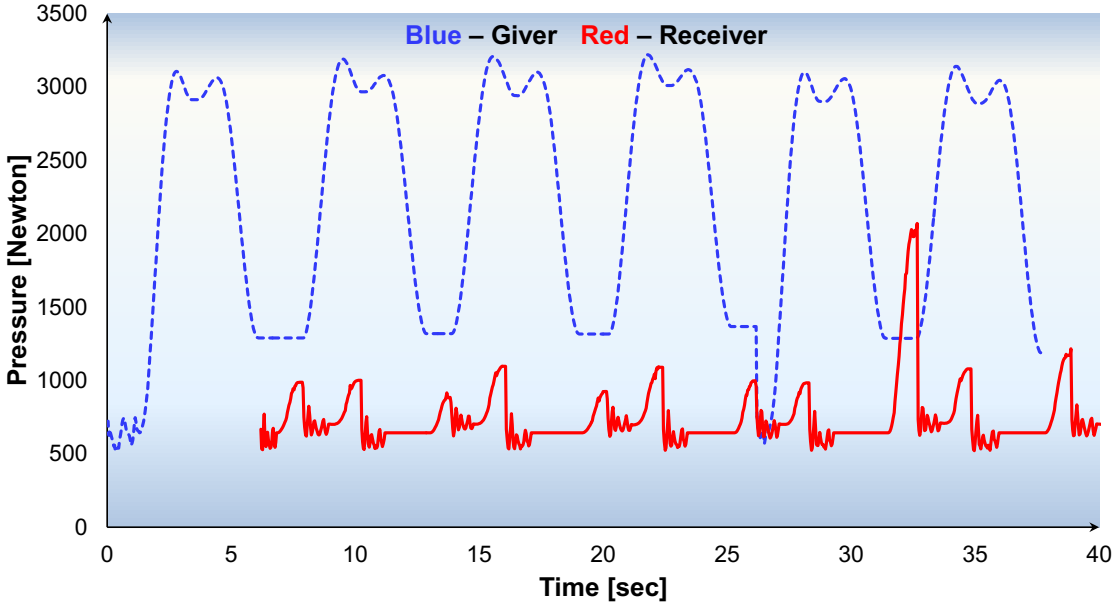



**Figure 4.2 The Lower Back Analysis (LBA) for a handover task (higher shelf)**

**Table 4.2 Simulation Results** showing the output of the Lower Back Analysis (LBA) indicating the average and maximum pressure sustained on the lower back for the giver and receiver for different shelf heights (Low/Medium/High) and for different population groups (5/50/95 percentile)

| Max pressure on the Lower Back in Newton (GIVER) | | | |
|---|---|---|---|
| **High** | Mid | Low | Shelf Height/ %tile of Population |
| **1855.21** | 1896.63 | 2011.15 | 5 |
| **2602.33** | 2610.38 | 2602.44 | 50 |
| **3220.87** | 3309.40 | 3411.50 | 95 |

| Max pressure on the Lower Back in Newton (RECEIVER) | | | |
|---|---|---|---|
| **High** | Mid | Low | Shelf Height/ %tile of Population |
| **1194.28** | 1300.51 | 1883.62 | 5 |
| **1598.45** | 2484.55 | 2399.33 | 50 |
| **2070.48** | 2186.89 | 3149.42 | 95 |

| Average pressure on the Lower Back in Newton (GIVER) | | | |
|---|---|---|---|
| **High** | Mid | Low | Shelf Height/ %tile of Population |
| **1276.68** | 1313.21 | 1318.58 | 5 |
| **1667.48** | 1664.92 | 1692.25 | 50 |
| **2203.01** | 2256.09 | 2245.90 | 95 |

| Average pressure on the Lower Back in Newton (RECEIVER) | | | |
|---|---|---|---|
| **High** | Mid | Low | Shelf Height/ %tile of Population |
| **453.47** | 471.55 | 788.07 | 5 |
| **634.80** | 794.12 | 999.25 | 50 |
| **744.52** | 725.14 | 1302.57 | 95 |

The underlying assumptions of this simulation study include the following:

a) The handover takes place in standing position.

b) The shelving of bottles takes place at a constant speed.

c) The point-of-handover between the giver and the receiver is fixed at 80 cm above the ground level.

d) The giver and the receiver are on the opposite sides of the matrix of bottles to be shelved.

e) The eye-gaze of both the giver and the receiver is fixed at the p-o-h during the handover process.

### 4.3.1. Results

Simulation results are presented in detail in Table 4.2. It shows the output of the Lower Back Analysis (LBA) indicating the average and maximum pressure (in Newton) sustained on the lower back for the giver and receiver for different shelf height (Low/Mid/High) and for different population group (5/50/95 percentile). Fig. 4.2 shows the Lower Back Analysis (LBA) of the giver (in blue-dashed) and the receiver (in red-bold) belonging to the 95-percentile population group during the course of the task of shelving bottles in the higher shelf. Figure 2 indicates that the peak to peak difference, $P_{Peak\text{-}Diff}$, in the sustained pressure (which is the difference between the variable's extreme values) between a giver and a receiver is 36%. The average pressure sustained by the giver is 2203 Newton (SD=825) and by the receiver is 774 Newton (SD=210), resulting an avg. difference $P_{Avg\text{-}Diff}$ of 65%.

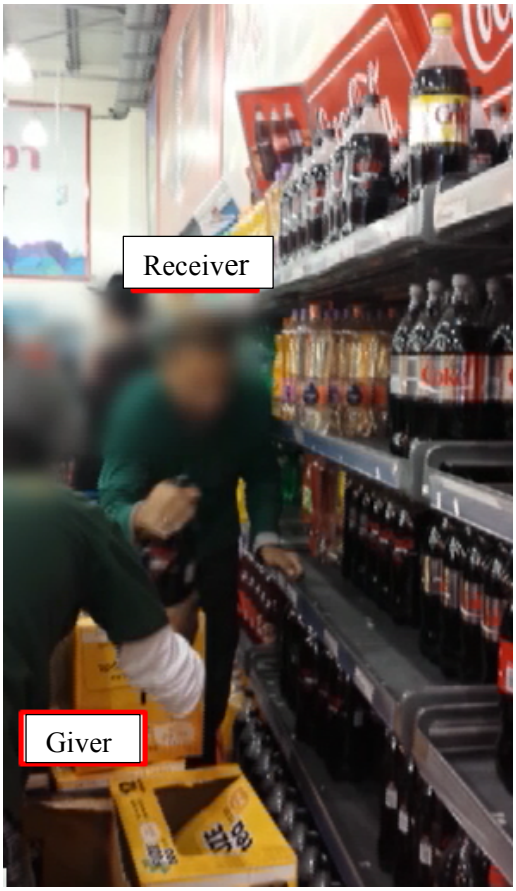
## 4.4. In-house lab experiments

### 4.4.1. Experimental design

*(1) The Scenario:* Figure 4.3 illustrates the real-life scenario of a supermarket that was re-created inside the IMT Robotics Lab of Ben-Gurion University of the Negev (BGU). The experimental area, as shown in Figure 4.4b, consisted of an empty shelf and a set of 120 soft-drink bottles of 1.5 liter filled with water, each weighing approximately 1.5 kg. The shelves used in the experiment were approximately of the same dimensions as those found in supermarkets (165 cm – upper shelf height, 124 cm – medium shelf height and 10 cm – lower shelf height). The given task was to fill the empty shelf with these bottles.

*(2) Conditions:* The experiment included two variables – shelf height (higher shelf/lower shelf) and frequency of handover (normal mode/competitive mode). In the normal mode, the teams were expected to work at a normal pace, without any time pressure or productivity target. In the competitive mode, teams were instructed to work faster than in the normal mode. The motivation behind the competitive mode was to simulate the peak hours/days of a supermarket prior to weekends or holiday seasons when the work pressure and the expected output increase considerably. Subjects were informed that the team with the highest throughput in the competitive mode will receive a prize. However, in either of the modes, no productivity target or time pressure was given.

**Figure 4.3 Field-studies done in this specific area of the supermarket**



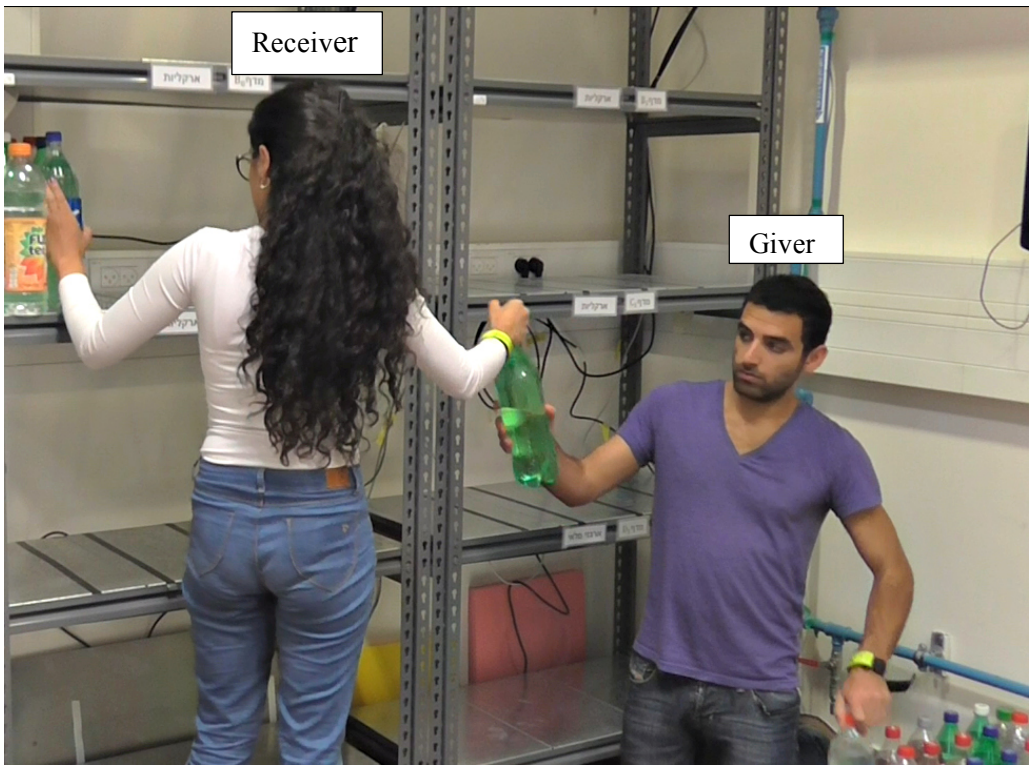




**Figure 4.4 Human-Human team-work in (a) the supermarket and (b) the experimental arena**

Furthermore, in both modes, subjects were unaware of the total time for which they are supposed to carry out the given task in each phase, the total number of bottles to be placed in the shelf and the total number of bottles in the inventory. They were informed that they need to continue until they were asked to stop. The motivation behind this was to ensure they should invest their energy smartly so that they are able to work for a longer stretch of time, since the goal was not to empty the inventory (because it is unlimited). In other words, the aim was to ensure a natural speed of work to resemble the speed of supermarket workers who do this job for a span of 8 hours.

The experiment had four phases, and each of the pairs went through all the four conditions: (i) Normal Mode – Higher Shelf, (ii) Normal Mode – Lower Shelf, (iii) Competitive Mode – Lower Shelf, (iv) Competitive Mode – Higher Shelf. The shelf height was assigned randomly; however, the competitive mode followed only after the normal mode was executed for both shelves.

*(3) Dependent Measures:* Participants' task-related performance was measured by objective analyses of the number of bottles shelved every 10sec during each phase and by off-line video data analysis of the joint-task, focusing on the level of coordination in the team during the task. The level of coordination was assessed by measuring the waiting time of the partner in every handover.

The number of bottles shelved every 10 sec measures the average throughput of the given pair. For each phase of the experiment, 12 measurements were taken (12x10=120sec; resulting in 2 minutes of each phase) for which the average productivity was derived. This process follows the central limit theorem in which the 12 random variables (each obeying the Poisson distribution) are distributed normally, regardless of the underlying distribution.

The analysis of participants' subjective experiences was based on two questionnaires, given during and after the experiment. Subjects were asked to report their experiences by ranking the current phase relative to the previous ones in terms of (i) comfort and (ii) coordination/synchronization during each of the intervals.

*(4) Participants:* A total of 42 participants (18 female, 24 male) took part in the experiment.

### 4.4.2. Results - Objective evaluation

Table 4.3 shows the average productivity (number of bottles/10sec) and variance of the different groups in the competitive mode (the first value in each cell) and normal mode (the

second value in each cell). The performance of all 21 teams for the lower and higher shelf is presented in the fourth and fifth row respectively. Results show that the average productivity in any shelf during the competitive mode and normal mode is approximately 8 and 5 respectively. The F-Test of equality of variances was done for different combinations of shelf height and speed/mode. The left and right curly brackets in Table 2 show a significance of $p<0.0001$.

The data was further analyzed and teams were classified into three categories, high-, average- and low-yield teams, based on their productivity in the competitive mode. Teams with an average productivity rate of 9 and above were categorized as high-yield (7 Teams), those between 8 and 9 as average-yield (6 Teams), and teams with 8 or less were categorized as low-yield teams (8 Teams).

The first three rows in Table 4.3 show the average productivity and variance of these three productivity-based categorized groups. Results indicate that the variance of the high-yield teams in competitive mode is significantly higher ($p<0.015$) than that of the low-yield teams by 43%. The high-yield teams in competitive mode are also the high-yield teams in

**Table 4.3 Average productivity rate (nr. of bottles/10sec) and variance for the competitive mode and the normal mode. The left and the right curly brackets show a significance of p<0.0001 (others are not statistically significant)**

| Group | Average productivity/10sec Competitive Mode/ Normal Mode | Variance Competitive Mode/ Normal Mode |
|---|---|---|
| High Yield | 9.60 | 2.73 |
| | 5.89 | 2.57 |
| Avg. Yield | 8.62 | 2.89 |
| | 4.97 | 1.37 |
| Low Yield | 7.23 | 1.90 |
| | 4.71 | 1.31 |
| Entire Group – Lower Shelf | 8.47 | 3.48 |
| | 5.08 | 2.06 |
| Entire Group – Higher Shelf | 8.37 | 3.45 |
| | 5.28 | 1.93 |

the normal mode, their productivity and their variance being significantly higher ($p<0.0001$) than that of the low-yield teams in normal mode by 25% and 96% respectively.

### 4.4.3. Results - Subjective evaluation

*1) Team communication during the task*

In response to the question on team communication that helped in increasing the mutual coordination between the partners, results (Figure 1 in Appendix A) show that the most frequent dialogues (39%) were concerning their relative positions to each other. Examples of such interactions include, "I stand here, and you go there". Other frequent exchanges were about the number of bottles to be transferred in subsequent handover. Together, they constituted 73% of all different types of communication.

*2) Perception of the Level of Difficulty of the task of the team partner when compared to oneself*

Results (Figure 2a in Appendix A) show that 95% of the receivers rated the level of difficulty of the giver's task compared to their own task, as having the same difficulty or being more difficult than theirs. However, only 23% of the givers say that the job of a receiver was "less difficult or easier" than their own. In fact, more than 70% of the givers said the task of a receiver has the same difficulty as theirs.

*3) How was the point-of-handover (p-o-h) decided?*

Subjects were asked in the questionnaire how the point-of-handover (p-o-h) was decided among them. Results (Figure 3.3 in Appendix A) show a difference in opinion between the givers and receivers. While 47% of the givers say they decided the subsequent p-o-h by looking at the location of the team partner's hand, an equal number of receivers did not bother to give a serious thought about the p-o-h because their perception of handover is "*it happened automatically, with no thinking*".

Figure 4.4, a still snapped during the in-house lab experiment clearly illustrates this observation. In addition, 33% of the givers and receivers say that they expected the p-o-h to be approximately at the same location as the previous handover.

*4) Habit persistence in decision making?*

Results (Fig. 2b in Appendix A) show that subjects tend to stick to their current roles if given a choice to switch (their roles) in a future experiment. 66% of the givers prefer to remain as givers and 90% of the receivers prefer to remain as receivers in future roles.

*5) Perception of the level of commitment of the partner towards the task*

Results (Table 1, Q5 in Appendix A) also show that 95% of the team members rated their partner as equally committed during the task.

*6) Relative ranking of the most comfortable phase and the most well-coordinated phase of the experiment*

Results (Figure 4 in Appendix A) show that 62% of all subjects generally felt most comfortable working in the normal mode. The lower shelf-normal mode was chosen as the favorite by the majority (67%) of the givers (Figure 4a) and the higher shelf-normal mode was chosen by 57% of the receivers (Figure 4b). Furthermore, results of the relative rankings of the best level of coordination (Figure 4) indicate that 30% (highest among the other options) of the givers rate the lower shelf-competitive mode as their favorites while 43% (highest among the other options) of the receivers rate the higher shelf-competitive mode as their favorites. In general, however, givers showed more diversity in choosing their favorites for the best level of coordination, as compared to receivers.

*7) Perception of the speed and rhythm of the partner and how they adapted to each other*

Results (Table 1, Q3 & Q4; Appendix A) indicate that most of the subjects (95%) noted they developed a rhythm and that they adapted themselves to match the speed of their partner. When asked about the perception of the speed of the partner, compared to themselves, Fig. 8 shows that 64% of the subjects considered their partner's speed as inconsistent (i.e., sometimes fast/sometimes slow). No giver is perceived as slower by the receiver and no receiver is perceived as faster by the giver (0%, Fig. 5 of Appendix A).

*8) Preference for using two hands (2 bottles at a time)*

Results (Table 3, Q2; Appendix) show that, if given a choice, 76% of the givers and receivers prefer to transfer 2 bottles at a time, as compared to one.

*9) Subjects' preferences towards working together or alone*

Results (Table 1, Q6; Appendix A) show that 90% of the subjects prefer to work in teams, even if that means they need to do double the work as a whole (100 bottles together), as compared to the option of shelving 50 bottles alone.

*10) Tendency when team coordination was perceived as perfect*

Results (Table 3, Q7; Appendix) show that no subjects (0%) felt the urge to slow down when they perceived that the coordination between them and their partner was perfect.

They either felt the tendency to speed-up (60% of the subjects) or maintain that speed (40% of the subjects).

*11) Fatigue*

Results (Table 4, Q8; Appendix) show that almost 85% of the subjects felt a level of fatigue that is equivalent to 'not at all' or 'a bit tiring'. Also, 95% of the subjects mentioned that the allotted break time between each mode was enough to recuperate from the tiredness.

### 4.4.4. Results – offline video analysis

*1) Point-of-Handover (p-o-h)*

Video analyses show that there is not always an eye-contact between the subjects at the p-o-h in every handover cycle. In these cases, the giver reaches up to the receiver's hand while the receiver extending his hand unconsciously to the previous p-o-h and keeping his/her gaze fixed towards the shelf.

*2) Location of the grasps on the bottle*

Video analyses indicated that when the subjects were delivering two bottles at a time, they tend to grasp the top part of the bottles. Whereas when the handover was one at a time, subjects tend to grasp the thicker bottom portion of the bottle. Also, when the bottle is transferred to the lower-shelf, subjects tend to hold the top part of the bottles and for the higher-shelf; it is seen that subjects tend to grasp the thicker bottom portion of the bottle.

*3) Negotiation in choosing roles in the joint-task*

Video analyses of the experiments shows that subjects mutually decided among themselves what role they want to choose and never had any disagreement during the negotiation; the negotiation was approximated to be achieved in less than 20 sec. The negotiation took place mostly non-verbally.

*4) Task expertise*

Video analysis indicated that the subjects slowly developed some sort of understanding in terms of team strategy and mutual speed of working, which resulted in better action coordination over time. This, however, did not remain constant and kept evolving, depending on the given experimental conditions (shelf height and mode).

## 4.5. Discussion

The research results allow us to draw several quantitative and qualitative conclusions related to human–human joint action in short-cycle repetitive tasks.

### 4.5.1. Objective analysis (compiling the results from all three methods)

Both the Jack simulation and the surveys of the supermarket workers indicate that *the task of the giver is physically more strenuous than the task of the receiver.* The maximum pressure on the lower back of a giver, belonging to the 95 percentile population group may go up to 3411.50 Newton (Table 4.2) which exceeds the threshold safety-limit for the lower back (Chaffin and Page 1994).

The average productivity rate in the experiment (5 in Normal Mode and 8 in Competitive mode; every 10 sec) was found to be similar to what was measured in supermarkets, confirming that the experimental data was collected in close to real conditions. Results (Table 4.3) of the objective analysis of experimental data indicate that the teams achieved higher productivity at the cost of higher variability in handover frequency. Lower values of variance among the low-yield teams indicate that the variability in handover frequency was lower, which in turn means the handover cycles were mostly stable, indicating good coordination. *This implies that the low-yield teams are in fact, the most well-coordinated teams.*

When the productivity of these three productivity-based groups was checked in normal mode, it turns out that the high- and low-yield teams in competitive mode continue to remain high- and low-yield teams in normal mode respectively. Variance of the high-yield teams are also significantly higher (96%, $p<0.0001$) than the other. **This means the art of well-coordination among the team partners is probably not influenced by the increasing or decreasing frequency of handover.** The well-coordinated teams continue to remain well-coordinated in either of the modes and vice-versa.

The existence of higher variability in high-yield teams can be explained, based on speed-accuracy trade-off of motor control in prehensile movements, which follows Fitts' Law (Serfaty et al. 1998). As the speed of the team partners increased, the point of handover kept moving (from L to R or from R to L along the length of the shelf) at a faster rate, which might influence the variability following Fitts' Law. Since increased variability resulted in poor-coordination, 'accuracy' is in a sense compromised here.

The variability in handover frequency may also be attributed to the evolving team dynamics and bottle placement strategy. In other words, the differences in the way the bottles are placed in the shelf and the number of bottles delivered in each handover may have an effect on the variability. Bottle placement strategy was not used as a metric to

measure variability because different teams came up with different strategies (each individual team sometimes even had different strategies for upper/lower shelves). As a result, it could be hard to classify this metric into a small 'n' number of categories to understand its role on productivity.

In addition, as observed during offline video analysis, when the expertise in handover grows over time during the course of the experiment, and participants are starting to develop some sort of coordination between them, variability tends to decrease. However, based on sec. 4.4.3.11, it can be said that there was no significant impact on the variability due to fatigue.

### 4.5.2. Subjective analysis

1) *Team Communication:* The communication among the team partners mostly consisted of interactions related to their relative position to each other. Research in sports psychology shows that when team members are in situations where verbal communication is feasible (in terms of physical distance, time taken to communicate, etc.), then inexperienced teams prefer to communicate task–specific knowledge through intentional verbal communication, to ensure high-levels of accuracy of the message transfer (Serfaty et al. 1998; Eccles and Tenenbaum 2004; Richardson et al. 2005; Galati and Avraamides 2013). Considering that the subjects were doing the given job for the first time, the observation can be related to the above explanation.

2) *Modesty influences Team dynamics*: **Almost every subject considered their team partner as equally committed towards the task.** This probably influenced the way subjects rated the relative difficulty level of the task of the other (Table 1, Q5, Appendix A). This observation can be interpreted, in other words, as both partners in more than 90% of the teams showing a level of modesty when rating their partner's performance.

Support for this result can be found in applied psychology research where it has been shown that at an individual level of analysis, personality traits like agreeableness have a major influence on *peer-ratings* of team member performance (Bernardin et al. 2000), irrespective of job-specific skills and general cognitive ability (Neuman and Wright 1999). Results show that 95% of the team members rated their partner as equally committed during the task, indicating a good level of agreeableness (the tendency to be good-natured, cooperative, and trusting) between the partners in our experiment.

3) *Habit persistence in Decision Making*: Even though the job of a giver is apparently and ergonomically more difficult than that of a receiver, the majority of givers opted to stick to their current role (Fig. 2b in Appendix A). This observation is generally explained by psychologists, using the theory of habit persistence in decision-making (Dynan 2000; Haaijer and Wedel 2001; Thunholm 2004). According to this theory, habit plays a certain role in decision-making. In our experiment, subjects spent only 20 minutes on the task (including break sessions), and even in this limited time clear signs of habit persistence were indicated. So, it can be concluded that habit-persistence in decision-making is a phenomenon that can occur even in repetitive handover tasks of smaller durations.

4) *Emergent Coordination*: **Subjects on the one hand were inconsistent** (Fig. 5 in Appendix A)**, and on the other hand, they were rhythmic** (Table 1, Q3 & Q4; Appendix A**)**. This observation of adapting themselves to form a rhythm is termed as emergent coordination (Knoblich et al. 2011) by the psychologists, where the partners sometimes speed-up or slow down, depending upon the context, to match their partners' speed, giving rise to a rhythm between the partners.

5) *Leading and Lagging:* Analyses of the results of the subjects' perception of the speed of the other (Fig. 5 in Appendix A) indicate that givers were generally perceived as faster than receivers and vice-versa. Considering that movement synchronization is a guiding dynamical process, which leads to stable coordination patterns in natural human-human joint action, it can be concluded that **givers led and set the pace of coordination.**

6) *Does the most comfortable/ergonomic work method, when speeded up, create the perception of the most well-coordinated joint-action?*

**Subjects, in general, felt most comfortable working in the normal mode** (sec. 4.4.3.6). Such preferences can be easily explained on the basis of minimum bio-mechanical efforts and strain that one has to put-in for their chosen favorites. The Jack simulation study also shows that these modes offer the least fatigue and better ergonomics for their respective roles.

The relative ranking of best-coordination, however, shows that there exists a possible trend. **Subjects perceive the competitive mode of their most comfortable working mode as the most well-coordinated phase of the experiment**. We conclude from this observation that the act of perceiving the level of coordination among team partners may

not be the same for the same joint-action, because it depends upon their perceived effort, which again depends on the role of the subject.

7) *Preference towards* the *use of two hands:* From sec. 4.4.3.8, it can be concluded that **subjects in general have a preference towards using two hands together for the given task**.

8) *Negotiation in Decision Making*: A high level of agreeableness between the partners is probably the reason for such frictionless negotiation among team partners for choosing their individual roles (sec. 4.4.3.10). The agreeableness factor has its roots in applied psychology (Neuman and Wright 1999) and has been explained above in the discussion section under sec. 4.5.2.2 – Modesty influences Team dynamics.

9) *Preference towards working in Teams*: From sec. 4.4.3.9, we conclude that **subjects have shown clear preference for working in teams.**

10) *Rhythms that speed us up:* Support for the behavioral tendency of the subject, when the team coordination was perceived as perfect, can be found in research in Musicology and Psychology, where it has been shown that **humans feel the urge to speed-up under certain rhythms** (Sanabria et al. 2011). The current observation is in line with these findings and has implications for adaptive control system design, which is discussed in the next section.

11) *Point-of-Handover:* Results (sec. 4.4.3.3) indicate that the decision on handover point is taken sub-consciously or automatically by the giver / receiver in many of the cases. In other cases, both receiver and giver expect the handover to take place around the same location as the previous handover. In other words, the anticipation of the p-o-h of the subsequent h/o in short cycle repetitive task is based on the experience of the previous handover.

It is to be noted that the handover in the experiment is facilitated without necessarily having eye-contact between the giver and receiver (sec. 4.4.4.1). So the p-o-h is not necessarily determined by the giver, as in (Basili et al. 2009), but it varies in this experiment. For example, when the giver and receiver do not have eye-contact, then the p-o-h is unconsciously decided by the receiver as the giver reaches up to the receiver's hands (while the receiver extends a hand unconsciously to the previous p-o-h and keeps his/her gaze fixed towards the shelf). This observation supports previous findings that in repetitive

handovers, a-priori expectation of the receiver about the probable p-o-h plays an important role in the success of the handover (Huber et al. 2013)

12) *Location of the grasps on the bottles:* Results of sec. 4.4.4.2 can be explained based on the end-state comfort effect governing motor control which predicts that "people will grasp an object for transport in a way that allows joints to be in mid-range at the end of the transport" (Rosenbaum et al. 1990; Rosenbaum et al. 1996). It also supports previous findings (Cohen and Rosenbaum 2004; Meyer et al. 2013) that this observation is probably a distinct effect of recall and generation on movement planning, and that the end-state comfort effect facilitates joint-action (Herbort et al. 2012).

## 4.6. Control system design implication

A-priori expectation of the receiver about the probable p-o-h plays an important role in the success of the handover in a short-cycle repetitive task (sec. 4.5.2.11). Section 4.5.1 revealed that well-coordinated teams continue to remain well-coordinated in all the tested conditions, and hence they have the least variability in their handover frequency.

In the case of a short-cycle repetitive task in supermarkets, where duration of each handover cycle could be as low as 2-3 seconds, generating 100% accurate adaptive motion and determining the exact p-o-h for each handover cycle through action coordination based on Keller's framework (Repp and Keller 2004; Keller and Koch 2008) of adaptation, attention and anticipation will generate non-rhythmic motions (due to processing times involved in delivering high accuracy) resulting in a stop-and-go motion with no fluency in joint action. This may potentially have a high cost on team coordination and productivity.

Based on the findings of sec. 4.5.2.11 and 4.5.1, it is argued that if team productivity is deemed critical for a human-robot system, executing a short-cycle repetitive task, **a robot with a fixed periodic motion and a fixed p-o-h, pre-set by the respective user, is probably better suited than highly accurate systems with non-rhythmic or reactive motions.** This is because, a robot working with a fixed rhythm is more well-coordinated and predictable than any other system. So, mutual coordination can be easily achieved through human adaptation, because humans are considered experts in working jointly in rhythmic activities. A recent study has also shown that human adaptation in a human-robot system can significantly improve team collaboration (Nikolaidis et al. 2016).

The robot should, however, be equipped with advanced sensors to be able to track the human partner as a whole for valid safety reasons. Also, the robot must be able to understand that the job is over / at pause and should not blindly continue the fixed rhythmic motion for indefinite time.

This type of fixed rhythmic robot motion is similar to the pro-active behavior, as demonstrated in a human-robot repetitive handover experiment (Huang et al. 2015). Results (Huang et al. 2015) show that the proactive method provided the greatest levels of team performance, but offered the poorest user experience, compared to the reactive and adaptive methods. The reactive motion offered the best user experience but the worst team performance, while the adaptive motion offered a balance of the two requirements.

In a fixed rhythmic H-R interaction, the user should ideally be given the opportunity to pre-define the robot's periodic motion and the p-o-h during the learning by demonstration phase, to ensure that the user is very much in control of the desired speed and p-o-h. This could offer a somewhat better user-experience and may offset the poor user experience involved in such pro-active behavior. A recent study (Sun and Sundar 2016) shows that the possibility to customize the interaction with a robot as per one's individual preferences creates a sense of "self-agency" in humans, which has a strong positive influence on user-experience.

# Chapter 5 | Human-Robot Collaboration Taxonomy and Models

***Chapter Overview***

The taxonomy of a H-R collaborative system is discussed in this chapter. The influencing parameters of a H-R collaborative system and its broad classification into three groups is discussed in detail with examples. Based on the preliminary principles of how humans perceive and process time in a handover task, analyzed in the previous chapter, three human-robot collaboration models – timing, sensor and adaptive – were developed for fluent and intuitive team-coordination in handover tasks. These models are discussed in detail in this chapter.

## 5.1. Influencing parameters of H-R collaboration

An H-R collaborative system is influenced by many parameters that affect its performance (Bechar and Edan 2003; Bechar et al. 2009; Oren et al. 2012). In this dissertation, the parameters were classified into three main groups, based on the source of origin of each influencing parameter: collaboration design, task and agent-intrinsic (Someshwar et al. 2012a). Different combinations of all these parameters for a given dynamic environment can give rise to different types of dynamic scenarios.

### 5.1.1. Collaboration design parameters

Parameters that are connected to the design of the workspace and to the collaboration aspects fall into this category. These include, for example:

*Buffered or non-buffered coordination:* Existence or non-existence of a buffer between a human and a robot can influence the human´s and/or the robot´s waiting times during a coordination process. The buffer capacity also plays an important role.

*Single agent or multi-agent:* The presence of a single or multiple robots in the collaborative task also influences the overall performance. Examples of multi-agent scenarios when there are, let's say, two humans and two robots involved in the process could be (i) a cycle consisting of human-robot1 and then robot1-robot2, (ii) a cycle consisting of human-robot1 followed by human-robot2, (iii) a cycle consisting of human1-robot1 followed by robot1-human2.

Mathematically, we can define these multi-agent scenarios using an allocation matrix a, such that:

$$a_{i,j} = \begin{cases} 1 \cdot if \text{ human and robot are collaborating} \\ 0 \;\; if \text{ H - H or R - R is collaborating} \end{cases}$$

<u>*Coordination protocols:*</u> These are the pre-defined and explicit 'rules of collaboration' between the partners in a mutually dependent task. It is pre-defined on the basis of the workspace design and task objectives. Two distinct coordination protocols were investigated in this research:

*Protocol 1* – Whoever comes first waits for the other; (relevant for single agent-singly tasked scenario, e.g., one human and one robot)

*Protocol 2* – Robot never waits for the human but continues its periodic cycle. The human, however, when arriving earlier, will wait for the robot (relevant for multi-agent multi-tasked scenario, e.g., 2 human and 1 robot or 2 humans and 2 robots)

In the first case, whoever arrives first waits for the other at the spatial point of handover until the handover is executed successfully. As a result, there is no cumulative error in this mode of coordination, because the earliness or tardiness of the human/robot in one cycle does not affect the subsequent cycles. It is relevant for single agent-singly tasked scenario, e.g., one human and one robot.

In the second protocol, the robot never waits for the human at the point of handover but continues its cycle of periodic movement if the collaborating partner is not arriving at the right time. The human, on the other hand, waits for the robot if it happens to arrive earlier. Therefore, if the handover is not successful in the first attempt, the human waits for the second turn of the robot to repeat the same action. Such a protocol can be very useful for a scenario where a multi-tasking robot is employed that is responsible for additional jobs besides collaborating with the human or if the robot is collaborating with two or more humans, e.g., in scenarios investigated in (Ding et al. 2013).

### 5.1.2. Task parameters

Parameters that are connected to the design of the task fall into this category. These include, for example:

<u>*Exclusive task or shared task:*</u> An exclusive task exists if each of the participants in the collaboration is responsible for an individual task and the act of collaboration exists only at

the point of handover (Someshwar et al. 2012a); e.g., assembling of electronic circuit boards done by the collaborating robot and quality inspection is done by the human). When the joint-task requires the collaboration of each of the participants at every subsequent step of its execution, it is called a shared task (Someshwar et al. 2012a); e.g., drilling of holes in an assembly piece is done by the robot, and fixing of nut-bolts in the respective holes is done by the human.

*Repetitive process or a one-time handover:* Repetitive processes are those in which the human and the robot work collaboratively repeating the same sequence of actions over a considerable period of time (Someshwar et al. 2012a); e.g., assembly operations in a manufacturing industry. In such cases, the accumulated temporal delay in the last cycle may have an effect on the subsequent one, and over a period of time it may result in a cumulative effect. In one-time handovers, the human-robot collaborative act is just a one-time process and the subsequent collaborative action has no correlation with the previous action (Someshwar et al. 2012a); e.g., a robot delivering a drink to a guest when the robot serves as a waiter.

*Task length:* Two types of repetitive tasks are analyzed in this research – short-cycle and long-cycle. A short-cycle repetitive task is defined as a physical task done by a human with an individual cycle length of the task / sub-task varying approximately between 2 sec (or less) to a maximum of 20 sec (Garg et al. 2006; Bosch et al. 2012; Wilcox et al. 2012). The lengths of long-cycle tasks have not been defined precisely in the literature; for this research, any job with the cycle length of the task / sub-tasks exceeding 20 sec has been classified as a long-cycle task.

*Task complexity*: As per (Byström and Järvelin 1995), "The literature suggests many task characteristics related to complexity: repetitivity, analyzability, a priori determinability, the number of alternative paths of task performance, outcome novelty, number of goals and conflicting dependencies among them, uncertainties between performance and goals, number of inputs, cognitive and skill requirements, as well as the time-varying conditions of task performance (Campbell, 1988; Daft et al., 1988; Fischer, 1979; Fiske & Maddi, l961; Hart & Rice, 1991; Javelin, 1986; March & Simon, 1967; MacMullin & Taylor, 1984; Tiamiyu, 1992; Tushman, 1978; Van de Ven & Ferry, 1980; Wood, 1986; Zeffane & GUI, 1993)". In the current research, one of these characteristics – temporal variability in task performance – has been considered to define task complexity.

### 5.1.3. Agent-intrinsic parameters

The inherent characteristics of the participating agents (human and robot) in a collaborative task can be defined as agent-intrinsic parameters (Someshwar et al. 2012a). Below three examples of such parameters are discussed.

*User-proficiency:* Two levels of user-proficiency are analyzed in this research – novice and expert. A novice user, in this research, is characterized by a collaborating partner with large variation in their average time of arrival at the point of handover. Similarly, an expert user-profile is characterized by smaller variation and greater consistency (compared to a novice user) in their average time of arrival at the point of handover during a repetitive process (Someshwar et al. 2012b). This will change with training and time.

*Learning (speeding up) or fatigue (slowing down):* The robot may learn from its previous handover experiences and may anticipate its subsequent action better over time. It can improve the accuracy of its time of arrival at the point of handover. Similarly, the waiting time may reduce through human learning or training. The collaborating human may also feel fatigue over time, and this may slowly change the handover cycle time. The effect of the user speeding-up / slowing down over time when performing repetitive H-R handover tasks was analyzed in this research as learning and fatigue respectively.

*System reliability:* The system reliability variable takes into account the various factors that affect sensor data accuracy and mechanical constraints (Someshwar et al. 2012a). System variables of a robot, such as sensor resolution, response time of sensors, resolution of the time-stamp, computation time, degree of freedom, repeatability, mechanical constraints and other agent intrinsic variables which affect a robot's reliable performance is included in the system reliability parameter. In a repetitive collaborative task, perceptual latency of the human (Seifried et al. 2010), temporal preparation (Bausenhart et al. 2010), and the rhythm of operation (Sanabria et al. 2011) can influence the coordination in H-R systems, and hence they are also included in the system reliability parameters.

## 5.2. The H-R collaborative manufacturing scenario

This dissertation investigates the problem of H-R collaboration in a repetitive handover task *(the task)* requiring temporal coordination among the collaborating partners when the external influencing parameters in the process are user-proficiency (an agent-intrinsic parameter), task length and complexity (task parameter), in a repetitive and exclusive

collaborative task (task parameter), for a single agent non-buffered interaction (collaboration design parameter), when there is learning/fatigue in the process (an agent-intrinsic parameter).

A typical industrial scenario was considered, where a human and a robot work collaboratively in a shared work-, time-space executing a common time-critical handover task (Figure. 5.1). Each of the partners is responsible for a discrete set of independent tasks. The collaboration happens in every H-R handover cycle with physical H-R interaction. From the right, the robot picks up the job from an assembly line (Figure 5.1a) and delivers it directly into the hands of the human (Figure 5.1b). The human receives it and inspects the

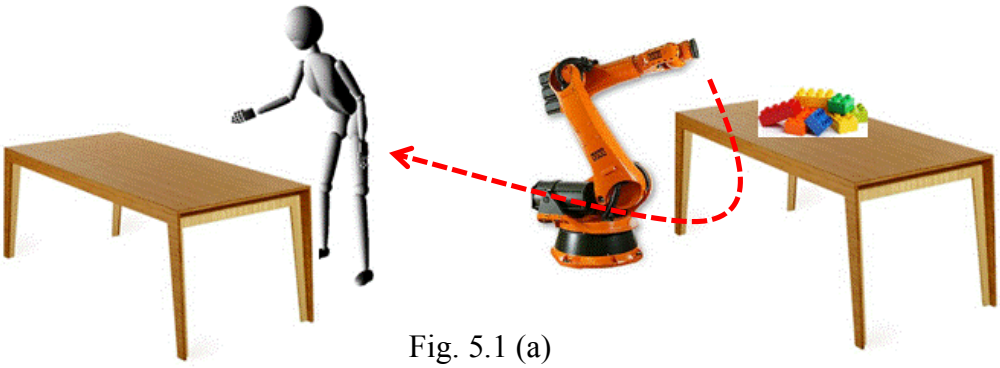


Fig. 5.1 (a)

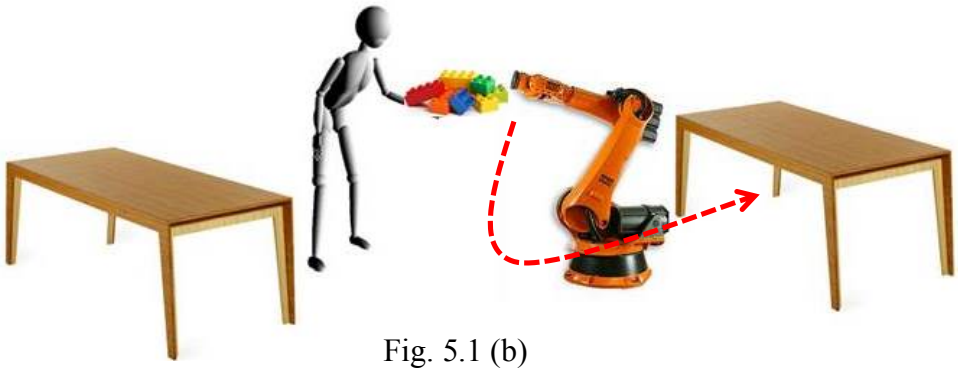


Fig. 5.1 (b)

**Figure 5.1 The Human-Robot handover task (a) Robot and Human is doing a discrete set of independent tasks, thereby preparing for the next H-R handover cycle; (b) Robot is handing over the job through physical human-robot interaction**

quality of the processed job and thereafter places it on another assembly line for packaging or in the defective lot. The process continues repetitively over time from right to left.

## 5.3. The H-R collaboration models

Three H-R collaboration models were developed for fluent and intuitive team-coordination in handover tasks, inspired by the way humans collaborate with each other in joint-actions with a common goal (Sebanz et al. 2006).

### 5.3.1. Timing control model

The operational cycle of robot actions is governed by only one parameter, time. The robot performs a series of pre-defined tasks at fixed intervals of time that is set by the end-user, depending upon the needs and operational demands of the scenario as shown in Figure 5.2a. The robot should, however, be equipped with advanced sensors to be able to track the human partner as a whole for valid safety reasons. Also, the robot must be able to understand that the job is over / at pause and should not blindly continue the fixed rhythmic motion for indefinite time. From a social perspective, this control model exhibits 'pro-active behavior', as demonstrated in a human-robot repetitive handover experiment reported in (Huang et al. 2015). An example where this model suits the scenario is a pick and place robot in an assembly station.

### 5.3.2. Sensor control model

The robot actions are initiated by a sensor signal. Two types of models are investigated in this research – the timing-based sensor model (Figure 5.2b) and the position-based sensor model (Figure 5.2c).

*Timing-based sensor model:* The robot enters the post-preparation or pre-action phase when the human sends a signal as he or she expects to finish the remaining part of the preparation in X seconds. For example, in an assembly station, where a human and a robot work collaboratively, the robot starts its preparation for the action when it receives this timing signal from the sensor.

*Position-based sensor model:* The robot will start its action when the human has reached a certain point in the action sequence. Using the example of the same assembly station, in this case the robot starts its preparation for the actual action when the human has just picked up the block from the assembly line that is to be delivered to the robot.

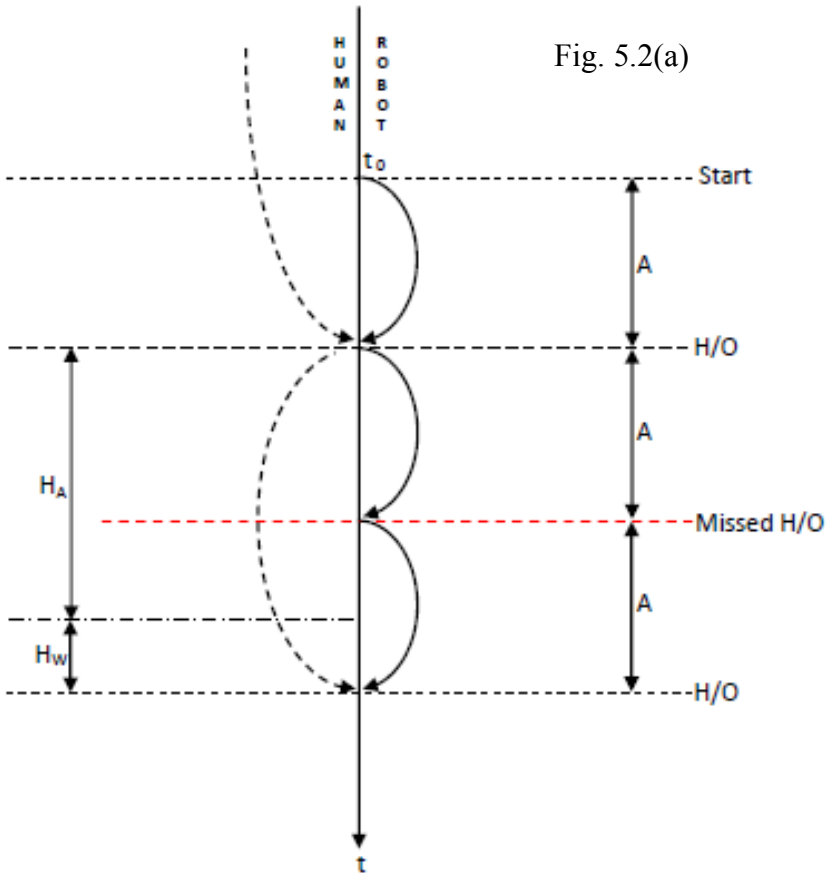



Fig. 5.2(a)

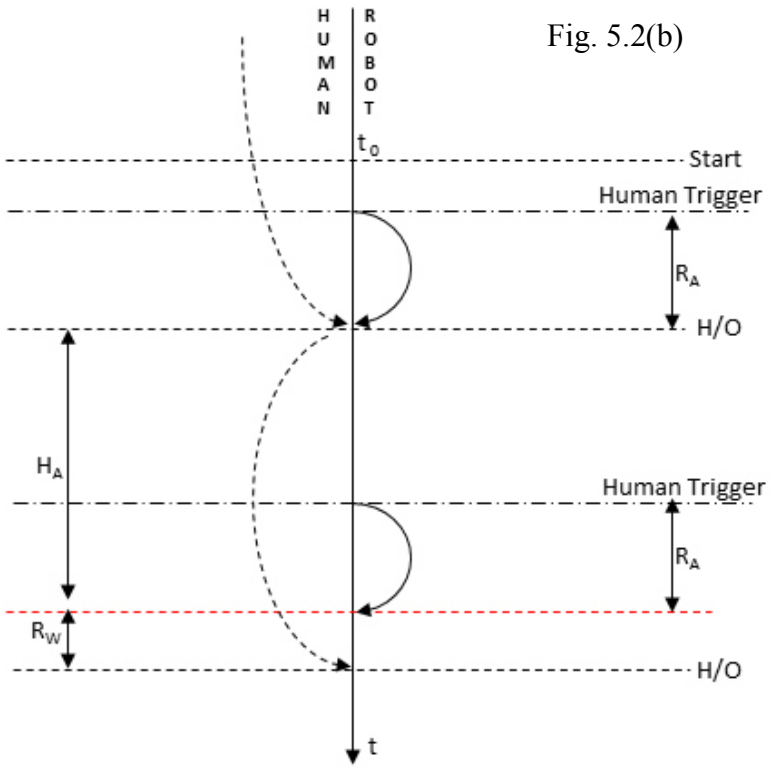
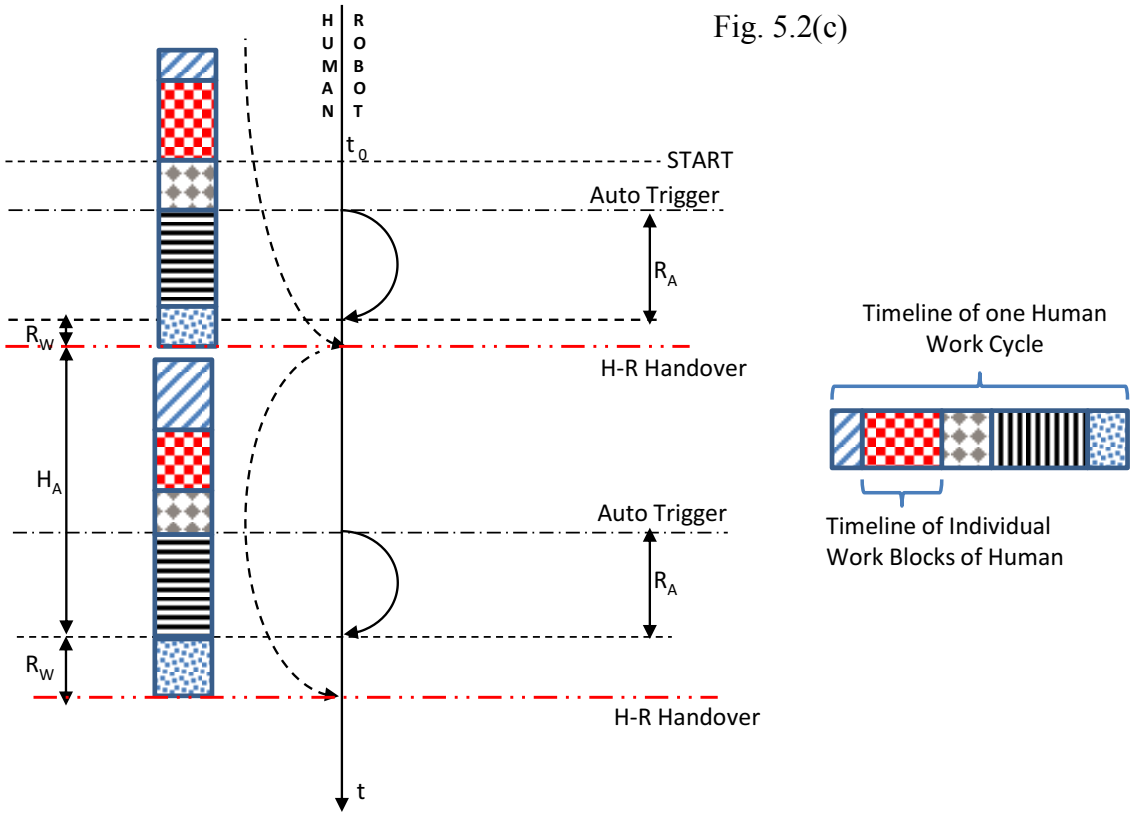



Fig. 5.2(b)




Abbr.: $H_A$/ $R_A$= Human / Robot Action Time, $H_W$/$R_W$= Human / Robot Waiting Time

**Figure 5.2 Human-Robot handover cycle during (a) timing control model (b) timing-based sensor control (c) position-based sensor control.**

### 5.3.3. Adaptive Model

This model is inspired from the human's ability to perceive, predict and adapt according to the changing rhythms and/or incoming temporal cues (Merker et al. 2009; Vesper et al. 2011; Keller et al. 2014). They allow humans to adapt in time with each other, giving rise to what psychologists call, emergent coordination. In a temporally adaptive model, the robot perceives, predicts and adapts in time to the rhythm of the human action. The perception, anticipation and adaptation are purely temporal in this model. The system does a time-series analysis of the past and incoming temporal data to anticipate the time of the next handover cycle.

**Sources of Temporal Data:** The following temporal data were used in this model:

(i) Temporal data of the handover cycle of all the previous end-users who collaborated with the robot for the given task (implemented in chapter 7 – exp. I, II, III).

(ii) Temporal data of the current end-user in all the previous handovers thus far (implemented in chapter 7 – exp. I, II, III).

(iii) Temporal data of the current end-user in the recent handover cycles. The temporal durations of the immediately preceding series of events have a strong correlation to the successive event (Madison and Merker 2005) (implemented in exp. I, II, III).

(iv) Temporal data of end-user for the recently done sub-task, when the given task is long and complex, and hence is executed in the form of multiple sub-tasks (implemented in exp III only).

**Table 5.1 The three H-R team-work experiments (Chapter 7)**

| Experiment Nr. | Experiment Title |
|---|---|
| Experiment I | H-R Collaboration in Long and Simple Task |
| Experiment II | H-R Collaboration in Short and Simple Task |
| Experiment III | H-R Collaboration in Long and Complex Task |

**Modeling the collaborating partner based on temporal data:** Based on the collected temporal data from all the aforementioned sources, the collaborating team partner is modeled in the following way:

(i) Naturally Fast/Average/Slow: This is computed by comparing the temporal data of the current end-user with the data generated by the end-users of the pilot experiment. If it is found that the current user is faster than the mean population in most of the handover cycles, then it is reasonable to categorize him/her as Faster. Similarly, users can be categorized as Average and Slow.

(ii) Accelerating Mode (Energetic)/Decelerating Mode (Fatigue)/ Relatively Stable Mode: This is computed recursively by comparing the variability in the temporal data of the current end-user for all the previous respective handovers thus far. Thereby, it can be checked if the person is in accelerating mode (energetic), decelerating mode (fatigue) or relatively stable mode.

In the case of a complex collaborative task (relevant for scenarios as described in Experiment III – Human-Robot Collaboration in Long and Complex Task), when the given task is not the same in every cycle, it is difficult to predict the variability of the end-user for the current sub-task of a given joint-task. This problem can be overcome to some extent by categorizing the given collaborative task, using the temporal variability data collected from the pilot experiments.

(i) *Task-level Categorization (Difficult, Average or Easy):* Based on the observed temporal variability among the subjects in the pilot experiment, the sub-tasks can be categorized as Difficult, Average and Easy. A task with higher temporal variability among subjects implies a difficult task, whereas tasks with lower variability among subjects imply an easy task.

(ii) *Task-length Categorization (Short, Medium or Long):* In a complex collaborative task, not all sub-tasks are of equal length. Some are of shorter duration, while others are longer. Such prior categorization of sub-tasks in terms of task-length (based on pilot experiments) helps in better temporal prediction as explained below.

**Expected System Behavior:** The deduced model of the collaborating partner can be combined with the concept of task categorization to generate an expected system behavior. For example, consider the following scenarios:

When the current end-user in accelerated mode finishes a supposedly difficult sub-task in less than the computed mean time (w.r.t the pilot subjects), then it is reasonable to predict that the same human will probably finish the subsequent difficult task faster. On the other hand, an end-user in fatigue mode will probably finish a long and difficult task, taking more time than the computed mean. Through this temporal reasoning, the robot can anticipate the next handover cycle more accurately, thereby taking into account the expected variability associated with a given task.

**Temporal Prediction Model***:* Based on the collected temporal data of the H-R system, the prediction model for a temporally adaptive H-R system is represented in generalized form by the following equation:

$$F = \alpha * D_T + \beta * D_S + \gamma * (\delta * P_n + \varepsilon * P_{n-1} + ..... + \theta * P_{n-q}) \qquad \textbf{Equation 5.1}$$

$n$- Number of handover cycles, $D_T$-general mean time of the population for execution of the given handover task, $D_S$- mean of the current end-user for the given handover task in all the preceding cycles, $P_n$- length of the handover cycle in the immediate 'q' preceding cycles.

The other variables alpha, beta gamma, theta, delta, epsilon are the weights of these parameters. This prediction model is suitable for short-cycle and long-cycle repetitive tasks where the given job is same in every cycle. It has been implemented as an adaptive model in Experiments I and II, respectively, and is presented in detail in chapter 7.

However, for complex collaborative tasks, the temporal prediction model was extended by incorporating the *Expected System Behavior,* which takes into account the expected variability in collaborating partners and the given task as shown in Table 5.2.

**Table 5.2 Expected system behavior based on temporal variability**

| EXPECTED SYSTEM BEHAVIOR | | | |
|---|---|---|---|
| Human Mode | Task-Length | Task-level | Prediction |
| Accelerated<br>Fatigue | Short | Easy | Zero Variability |
| Accelerated<br>Fatigue | Short | Difficult | Low Variability with chances of error<br>Low Variability |
| Accelerated<br>Fatigue | Long | Easy | Expected Early with low variability<br>Expected Delay with low variability |
| Accelerated<br>Fatigue | Long | Difficult | Expected Early with high variability<br>Expected Delay with high variability with chances of error |

The extended form of the equation can be written as:

$$P = F + \eta.Y \qquad \textbf{Equation 5.2}$$

where, $\eta = 1(Complex_Task)$
$\eta = 0(Simple_Task)$

$$F = \alpha * D_T + \beta * D_S + \gamma * (\delta * P_n + \varepsilon * P_{n-1} + ..... + \theta * P_{n-q})$$ **Equation 5.1**

$$Y = \theta.W + .\Omega.ESB$$ **Equation 5.3**

where, W = Deviation in the immediately preceding Sub-Task

ESB = Expected System Behavior

Ω = 1 [prediction is as expected];

Ω = 0 [no prediction possible]

F = the predicted value

*n* = number of sub-tasks done (assembled)

$D_T$ = general mean of population for assembly of one cube

$D_S$ = mean of the current human for assembly of one cube

$P_n$ = mean of assembly time for the-n cube

The value of Ω varies between 0 and 1, depending on its predictive accuracy in the previous handover cycles. Equation 2 is the generalized form of the temporal prediction model, which has been adapted accordingly in the three experiments, as detailed in Chapter 7.

# Chapter 6 | Analytical and Simulation Studies

***Chapter Overview***

Analytical (Part A) and simulation studies (Part B) of a Human-Robot (H-R) team collaborating in a repetitive handover task were performed. Temporal fluency of the H-R coordination was used as the system performance measure. The influence of user-proficiency (novice/experienced), prolonged work periods (learning / fatigue over time) and system reliability (the various factors that affect sensor data accuracy and mechanical constraints) for different co-ordination protocols were evaluated through six case-studies. The results of the case-studies are discussed with system design implications. The chapter concludes with the comparative analyses of the two analyses methods and of the H-R collaboration models.

## Part A – Analytical Study

A typical industrial scenario, as described in Chapter 5, was considered where a human and a robot work collaboratively in a shared work-, time-space executing a common time-critical task. Each of the partners is responsible for a discrete set of independent tasks. Collaboration occurs in every H-R handover cycle with physical H-R interaction. The robot picks up the job from an assembly line (Figure 5.1a) and delivers it directly into the hands of the human (Figure 5.1b). The human receives it and inspects the quality of the processed job and thereafter places it in another assembly line for packaging or in the defective lot. The process continues repetitively over time. H-R teamwork fluency for this scenario was investigated using an analytical approach described below. To illustrate the application of the analysis methodology, two case-studies were developed for which exact solutions were found for the given context. The case-studies differ in the way the human interacts with the robot, characterized as human delay distribution in a repetitive task.

### 6.1. Methodology

The system objective function was used as the H-R system performance measure to maximize the level of team-coordination (temporal fluency) between the partners for a given scenario. It was developed by taking into account the costs of human waiting and robot idle time in each work cycle using the following steps:

i. Model the problem in analytical language for the given protocol, thereby developing the problem statement.

ii. Take into account the agent-intrinsic parameters affecting a human, a random delay with (known) distributions was considered.

iii. Formulate the cost for human and robot in each periodic cycle.

iv. Develop the system objective function.

v. Determine the agent (human and robot) timing that minimizes the expected average cost.

## 6.2. Analytical analyses of timing-based control model of H-R system

Let us consider that the robot arrives at the point of handover at a regular interval of $A$ time units, and it continues its periodic motion repeatedly during the production cycle. Coordination protocol 2 is modeled in this analysis. Figure 6.1 shows the timeline of H-R collaboration during this coordination protocol. The optimized value of $A$ is calculated according to the solution of the optimization problem that is developed later in this section and solved in the form of case-studies I and II.

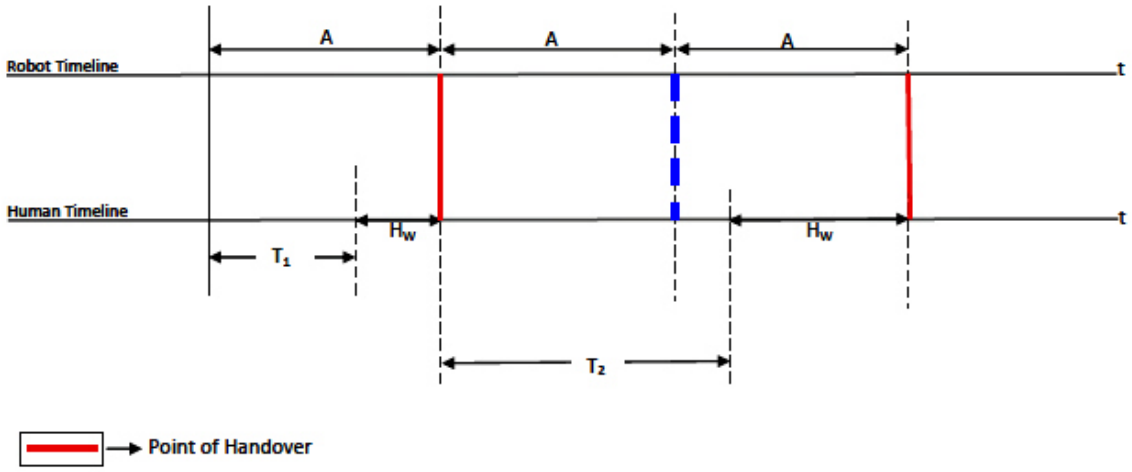



**Figure 6.1 The human and the robot timeline during H-R collaboration in timing-based control with the coordination protocol 2. The dashed blue line indicates the unproductive cycle**

### 6.2.1. The decision variables and influencing parameters

The decision variables are $t$, the time when the human is scheduled and $A$, the time between two consecutive visits of the robot. The influencing parameters are $C_R$, the cost for an unproductive visit of the robot, $C_H$, the human waiting cost per time unit and the function $F_Y(\cdot)$, the distribution of the human delay (while the random human delay is denoted by $Y$). We define a random variable $T = Y + t$ where $T$ is the actual human arrival time. The cost of waiting for the human $W$, is calculated as:

$$\boldsymbol{W = C_H\,[R(t) - H(t)]} \qquad \textbf{Equation 6.1}$$

$$\boldsymbol{W = C_H\,[A - T]\ for\ A > T} \qquad \textbf{Equation 6.2}$$

where $R(t)$ and $H(t)$ are the times taken by the robot and human respectively to complete one round of operation. When $A<T<2A$, that is the human misses the robot in the first robot operational cycle, then two types of cost comes into play – the human waiting cost, $W$, and the robot unproductivity cost, $U$.

In this case,

$$\boldsymbol{W = C_H\,[2A - T]\ for\ A > T > 2A} \qquad \textbf{Equation 6.3}$$

$$\boldsymbol{U_{Robot} = C_R\ for\ A > T > 2A} \qquad \textbf{Equation 6.4}$$

It is to be noted however, it is not necessary that the handover or the meeting between the human and the robot would definitely take place at the latest in the second operational cycle. Depending upon the value of $F_Y(\cdot)$, the time $T$ can vary from a value less than *'t'* and to a value far greater than $A$ and hence it may take many unproductive robot operational cycles.

### 6.2.2. The objective function of the H-R system

Given the decision variables $t$ and $A$, for any realization of $T$, the above expressions of the waiting/unproductivity costs of human and robot, respectively, can be rewritten in a more

generalized way as follows. The number of robot visits until the first productive one is $\left\lceil \frac{T}{A} \right\rceil$ where $\lceil a \rceil$ is the rounding up of a. Note that the cost of unproductivity per time unit is $\frac{C_R}{A}\left\lceil \frac{T}{A} \right\rceil$. The human waiting time, $W$ is then $A\left\lceil \frac{T}{A} \right\rceil - T$. Thus, the total expected cost per time unit of the H-R system is:

$$TotalCost_{System} = Cost_{HumanWaiting} + Cost_{RobotWaiting} \qquad \textbf{Equation 6.5}$$

Hence, the *objective function of the H-R system* can be expressed in the following way:

$$Cost(t, A) = E_T\left[ C_H\left( A\left\lceil \frac{T}{A} \right\rceil - T \right) + \frac{C_R}{A}\left\lceil \frac{T}{A} \right\rceil \right]. \qquad \textbf{Equation 6.6}$$

The solution of this optimization problem is to find $t$ and $A$ that minimize $Cost(t, A)$. Although, the inconsistency of human time is referred to here as "delay", this value can also be negative. This is because the human is sent to the station with the aim to be there at time $t$, but the human might rush and arrive earlier than $t$. In terms of the delay's distribution function, we mean that $F_Y(0)$ may be positive.

### 6.2.3. Exact solutions in case-studies

Two case-studies, as described in Table 6.1 were analyzed.

**Table 6.1 Analytical case-studies**

| Case-Study | Analysis Method | Control Model | Co-ordination Protocol | User-Proficiency |
|---|---|---|---|---|
| I | Analytical | Timing | Protocol 2 | Novice |
| II | Analytical | Timing | Protocol 2 | Expert |

#### Case-study I

Assume that $F_Y(y) = y$, i.e., the delay is uniform along the interval (0,1). Clearly, for any choice of $t$, the optimal choice of $A$ is between $t$ and $t+1$. Furthermore, any $t > 1$ will be sub-optimal, because with it either needless human waiting or an unproductive robot visit are guaranteed (a unit of time is simply lost in every cycle). The expected human waiting time by integration, given $(t, A)$ equals

$$\frac{A - At + t^2}{2} \qquad \textbf{Equation 6.7}$$

The expected number of unproductive robot visit equals

$$\left\lceil \frac{1+t}{A} \right\rceil \left( 1 + t - \frac{1}{2}\left( \left\lceil \frac{1+t}{A} \right\rceil - 1 \right) \right) - t \qquad \textbf{Equation 6.8}$$

The total cost of the H-R system is then

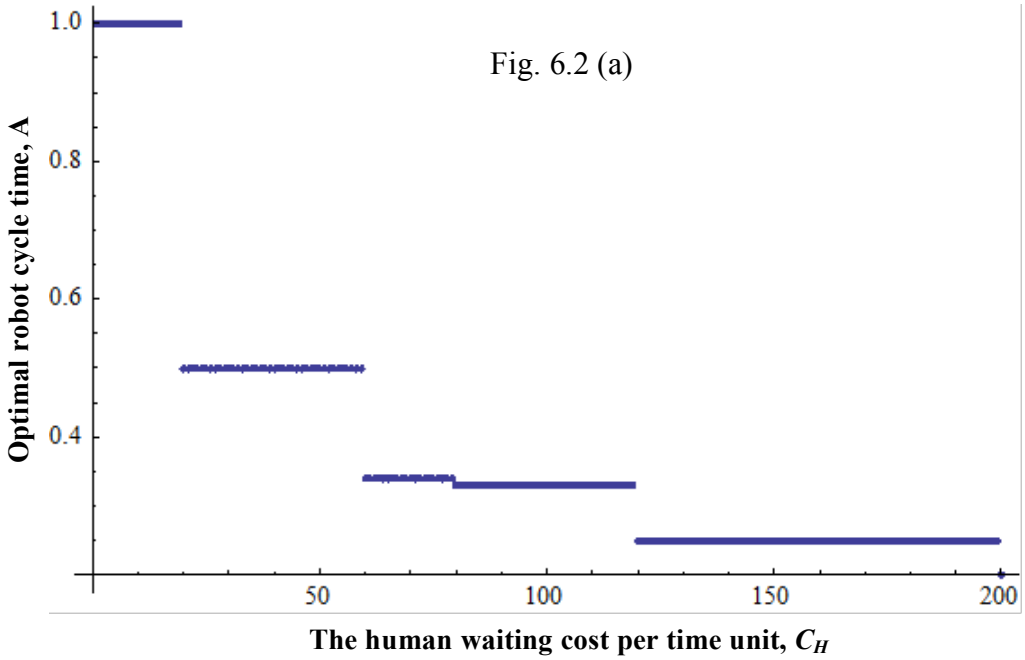
$$C_h \frac{A - At + t^2}{2} + C_r \left( \left\lceil \frac{1+t}{A} \right\rceil \left( 1 + t - \frac{1}{2}\left( \left\lceil \frac{1+t}{A} \right\rceil - 1 \right) \right) - t \right) \qquad \textbf{Equation 6.9}$$

Note that this function has discontinuities (since part of it includes step functions) which complicates the analysis. The optimal H-R system cost and optimal $(t, A)$ is presented in Figure 6.2, when the human cost $C_h$ ranges between 1 and 200 and the robot unproductivity cost is assumed to be constant with $C_r = 1$. Due to the uniform nature of the human delay, the optimal *t* equals 0 for any choice of the parameter. That is, *the human should aim at arriving as soon as possible*. Figure 6.2a indicates that for a certain range of values of $C_h$, the value of optimal *A* remains constant. Outside this range the change occurs in steps.

### Case-study II

This study focused on a solution for a different delay distribution of the collaborating human. One can assume that the human delay distribution follows an exponential distribution with rate 1 expressed mathematically as $F_Y(y) = 1 - e^{-y}$. Due to the memory-less property of the delay distribution, it is suboptimal to choose a value of *A* smaller than *t*. By simple integration, the expected human waiting time is calculated as:

$$A - (1+t) + \frac{Ae^t}{e^A - 1} \qquad \textbf{Equation 6.10}$$



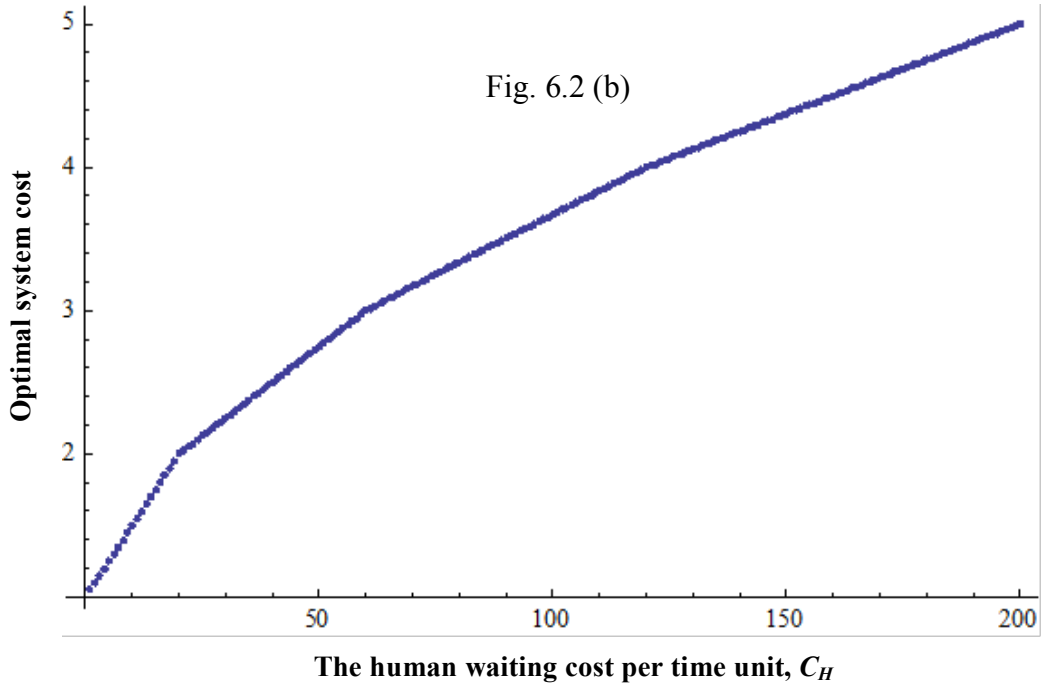




**Figure 6.2 Case-study I (a) The optimal value of $A$ as a function of $C_H$ (b) The optimal cost of the system as a function of $C_H$**

The expected number of robot visits until the first successful handover is equal to:

$$1+\frac{e^{t}}{e^{A}-1}$$ **Equation 6.11**

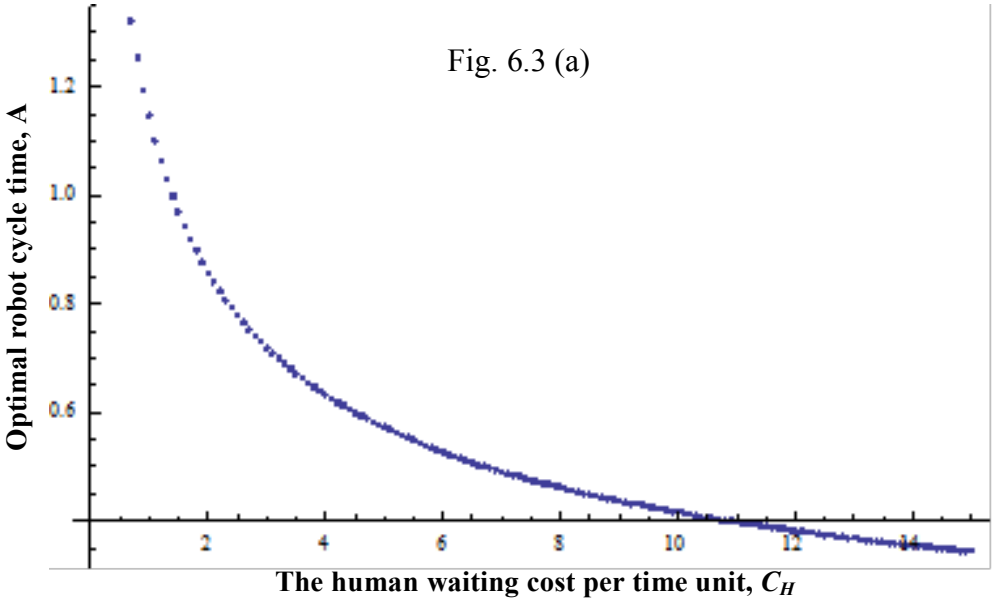
Results for values of $C_h$ between 0.1 and 15, while fixing $C_r = 1$ are presented in Figure 6.3 (note that the horizontal axis is not on zero). The optimal value of *t* turns out to be always *t=0*. This is because aiming for arriving at any time later than *t=0* will only add to the waiting time.

### 6.2.4. Discussion of case-studies

In Figure 6.2a (Case-study I), it can be seen that for a certain range of values of $C_h$, the value of optimal *A* remains constant and then the change is observed in steps. This result has direct implications on H-R control system design.

In repetitive tasks, if the human cycle time changes with time, as in case-study I, the H-R coordination is optimal when the robot cycle time (defined by *A*) does not change accordingly in every handover cycle. In this case, for a given bounded range of $C_h$, the robot cycle time must remain constant. This is when the timing-based control model is best suited for the operation of the H-R system. However, once $C_h$ exceeds a certain value, the robot cycle time must change/adapt accordingly. For this function, the H-R system needs sensor-based control, which could trigger the change/switch of the robot cycle time accordingly. It shows the importance of a future design of a hybrid control system, fusing timing- and sensor-based control models.

For novice users, whose arrival time at the point of handover varies greatly, this coordination strategy can assist in training with the system. It gives a novice user the chance to develop a working rhythm with the robot, as a fixed robot cycle time is predictable. For expert users, with low variability in their arrival time, a consistent speed of the robot supports better adaptation to the system. A recent study has also shown that human adaptation in a human-robot system can significantly improve team collaboration (Nikolaidis et al. 2016).



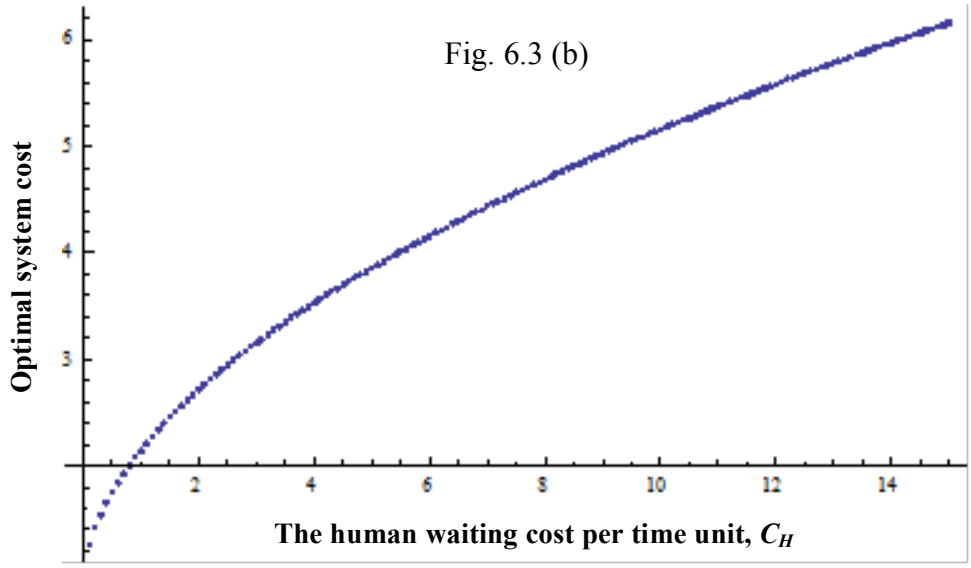




**Figure 6.3 Case-study II (a) The optimal A as a function of $C_H$ (b) The optimal cost of system as a function of $C_H$**

## 6.3. Analytical analyses of sensor-based control model of H-R system

In a sensor-based control model of an H-R system, the location of the sensor that informs the robot of the human's current state of action must be considered. The inclusion of this sensor in the system however, does not affect the analytical solution of the optimization problem. This is because, instead of estimating the total human action time distribution (as in timing-based control), now it is needed to estimate the human time distribution between

the action that triggered the sensor signal and the completion of the task. After estimating this distribution, the analysis is identical to the timing-based control model analysis.

Nevertheless, the total cost associated with sensor-based system should be compared to the one without them, and the value of installing a sensor is implied by this comparison. The following example demonstrates how optimization of sensor-based control of H-R system simplifies into an optimization problem similar to timing-based control.

Two tasks are performed sequentially, each by a different collaborating partner. The duration of the first task, performed by the human, is a random variable $X$ with the distribution function $F_X(x) = \Pr(X \le x)$. The second task is performed by the robot.

The aim is to place the robot in the place where the human completes the task (a known location), at the completion time. If the robot arrives before the human, there is a cost of $C_r$ per time unit of robot waiting. If the robot arrives after the human, there is a cost of $C_h$ per time unit of human's waiting. The optimization problem is when to locate the robot. If the robot is located at time $t$ then the total cost is,

$$\boldsymbol{U(t) = C_r(X - t)^+ + C_h(t - X)^+} \qquad \textbf{Equation 6.12}$$

where $a^+ = max\{a,0\}$, which is a random variable. In this case, minimizing $E(U(t))$ is the right criterion, for example because this process is repeated over and over, and hence the average cost is the point of interest. Mathematically, this problem is equivalent to one of the variants of the classical inventory problem called "the news vendor problem" (Laderman et al. 1953) and hence the optimal time $t$ is the solution of:

$$F(t) = \frac{C_r}{C_r + C_h} \qquad \textbf{Equation 6.13}$$

The optimal time is the percentile of the processing time distribution:

$$t^* = F^{-1}\left(\frac{C_r}{C_r + C_h}\right) \qquad \textbf{Equation 6.14}$$

Assume now that we can set a sensor that inspects the human at some moment during the task (or at some point along the route). Consequently, the distribution of the time from the sensing and until the human-robot action is not different and can be derived similarly to the

timing-based control model. Specifically, for every possible location of the sensor, some data needs to be collected and the relevant distribution should be estimated. Assume that there are *n* possible locations for the sensor. We introduce the following notations:

- $X_i$ is time needed for completing the task from sensing the human at location *i*.
- $F_i(x)$ is the distribution function of $X_i$ : $F_i(x) = Pr(X_i<x)$.
- $a_i$ is the cost of setting the sensor in location *i*.
- $t_i^*$ is the optimal time of locating the robot after sensing at location *i*.
- $u_i = E[C_r(X_i - t_i)^+ + C_h(t_i - X_i)^+ + a_i]$ is the total cost after installing the sensor at location *i*.

Let $u_0 = u_i = E[C_r(X_i - t_i)^+ + C_h(t_i - X_i)^+ + a_i]$ be the cost in the model without sensor.

The main problem is to solve whether to place the sensor and when the solution is positive, the location of the sensor must be determined. The solution for this problem is: set the sensor in location $i^*$ and locate the robot $t^*$ time units after sensing where,

$$i^* = arg\ min_{i=0...n}\ \{u_i\} \qquad \textbf{Equation 6.15}$$

We can see here that, $i^*$ and $t^*$ are identical to the optimization function of timing-based control. Hence, from the analytic point of view, sensor-based control is conceptually the same as the timing-based model, with the addition of another simple layer indicating the location.

## 6.4. Analytical analyses of adaptive control model of H-R system

In an H-R collaborative system that involves a repetitive task over a prolonged time-period, the human operator may slowly get tired over time due to fatigue. Novice operators' working speed may also increase over time as they develop task expertise and become proficient users of the system. For such a system, the robot should be able to adapt to the changing speed of the human. Such system needs can be easily met by deploying an adaptive control system in the robot that is able to adapt and change its speed in accordance to maintain the coordination between the human and itself.

However, the question that is investigated here is whether an adaptive control can yield higher productivity, compared to a timing-based control system, for a Human-Robot system

doing a prolonged repetitive task with coordination protocol 2 (robot continues its action, human waits if arrived earlier at the p-o-h).

### 6.4.1. The case of fatigue

To analyze the fatigue effect on the system, we assume that the human total time has an exponential delay distribution which represents the fatigue. Let *N* denote the total number of cycles. The human delay distribution *F(x)* is represented by the following equation,

$$F(x) = [\frac{\exp\frac{-x}{i}}{i}]$$ **Equation 6.16**

$$Unproductivity(A,\ t) = 1 + \frac{e^{t/i}}{-1 + e^{A/i}}$$ **Equation 6.17**

### 6.4.2. The case of human experience or learning

The human delay distribution *F(x)* in the case of experience or learning can be represented by the following equation,

$$F(x) = [\exp(-x.i)].i$$ **Equation 6.18**

$$Unproductivity(A,\ t) = 1 + \frac{e^{t.i}}{-1 + e^{A.i}}$$ **Equation 6.19**

### 6.4.3. Discussion

Figure 6.4 (a and b, respectively) indicates the percentage increase *(Δ)* in the productivity of the adaptive system, as compared to a timing-based control system for robot cost $C_r$= 15 when there is fatigue or learning in the process. In the case of fatigue, the increase in productivity is only significant (6%) for the first 20 cycles (between *N*=1 and 20), and thereafter, with the increasing number of cycles (between *N*=20 and 50), indicating prolonged collaborative work periods, the productivity increase is only 1%. The system behavior in the case of learning is also the same. The productivity increase is 3.8% for the first 10 cycles, and thereafter the difference is almost negligible (only 0.2% for the next 10 cycles between *N*=10 and 20).

For the given condition, adaptive control does not offer a significant advantage over timing-based control in terms of productivity for a Human-Robot system doing a prolonged repetitive task with coordination protocol 2. The conclusion can, however, not be generalized, as it depends on the human delay distribution and the adaptive control model performance.

## 6.5. A practical case-study of a pallet manufacturing system

A pallet[1] is the structural foundation of a unit load which allows handling and storage efficiencies. The pallet manufacturing process is semi-autonomous[2] and an example of a human-robot collaborative repetitive task. A real life application of the above described analytical methodology to improve team-coordination is shown below.

### 6.5.1. Description of the scenario:

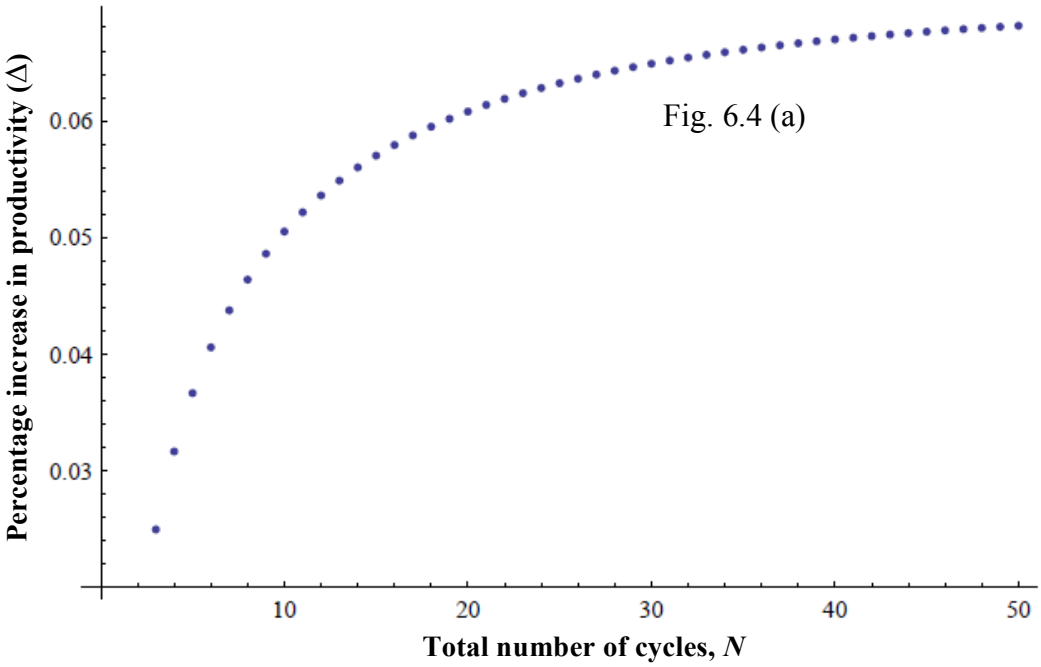
In this pallet assembly station, the robot does the difficult and dangerous work of nailing the wooden pieces and the human does the job of laying the wooden pieces into the respective frame. The square frame is placed on a rotor-base that turns the frame once on the human side (when wooden frames are being laid) and the other time on the robot side (when it nails the wooden blocks, thereby building up the pallet). The cycle time of the rotor is 70 sec (raw data collected online from an assembly station of Jointec AB[3], Sweden).

Assume the human takes roughly 35 seconds for its task of picking up wooden blocks from a pile and laying it in the frame in the correct order and the robot takes 35 seconds to nail down and then place the finished product over the stack of finished pallets. The human-robot collaborative work continues following coordination protocol 2 for a period of 8 hours every day.

### 6.5.2. Analytical system modelling

Since this is a case of collaborative work, the human and the robot could devote their time to the assembly station for a fixed time period of length $T$ (say a working day). Under this assumption, the determining factor influencing the joint-productivity of the system is the length of an individual cycle. The aim is to produce a maximal number of pallets per day.

[1] Definition - https://en.wikipedia.org/wiki/Pallet
[2] https://www.youtube.com/watch?v=6BSF2146wj4
[3] http://www.jointec.se/



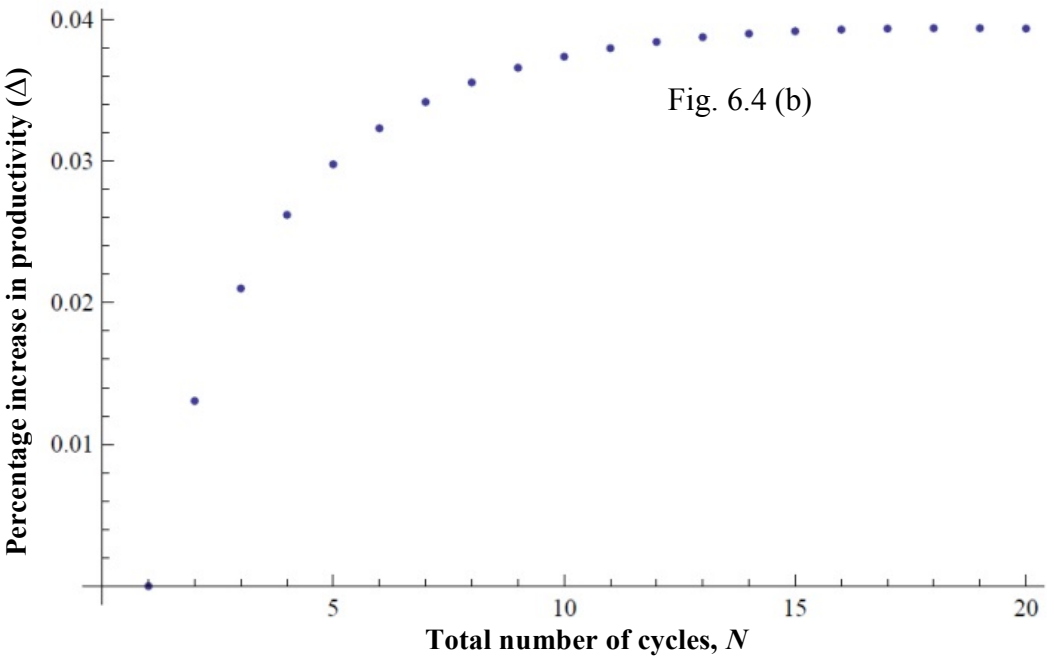




**Figure 6.4 Percentage increase in productivity (Δ) of the adaptive system as compared to timing-based control system Vs. the total number of cycles *(N)* in a repetitive task for changes in (a) the case of fatigue (b) the case of learning**

**Figure 6.5 A Human-Robot cooperative pallet assembly station (picture courtesy: Jointec)**

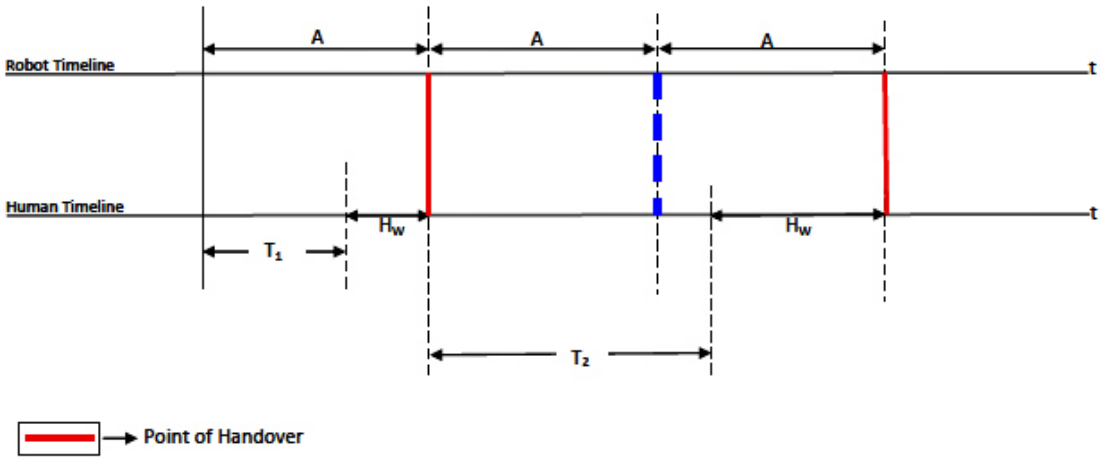



**Figure 6.6 The human and the robot timeline during an H-R collaborative task. The blue line indicates an unproductive round**

Therefore, there is an obvious incentive to have a shorter cycle. However, a too short cycle may result in an unproductive cycle which implies a cost (e.g., a too short cycle may cause human error which may increase the number of defective pallets). The decision variable is therefore the length of a cycle denoted by *A*. The influencing parameters of this collaborative system are:

a) The length of the interval ($T$) (not so relevant because in any reasonable cost function, $T$ will be a multiplicative constant).
b) The cost of unproductive collaboration for one cycle *(c)*.
c) The distribution of the time required for the human to perform his task (denoted by a probability density function $f$ and cumulative distribution function, $F$).

### 6.5.3. System objective function

Let $X_1, X_2, \ldots$ be the (random) times required by the human operator to finish his task. Given a cycle length $A$, $c$ is the cost of the H-R system as a combined entity, the utility function of the system is calculated as:

$$\sum_{i=1}^{T/A}\left(1_{\{X_i<A\}} - c1_{\{X_i>A\}}\right) = (1+c)\sum_{i=1}^{T/A}1_{\{X_i<A\}} - \frac{cT}{A} \qquad \textbf{Equation 6.20}$$

$X_i > A$ denotes the cases when the length of the current cycle is greater than the fixed cycle of length $A$ ($X_i$ is greater means human took more time to finish his task and as a result the robot had to wait for the human at the point of handover). All such cases will result in a fixed cost of value $c$. The total number of possible cycles (in ideal case) can be obtained by dividing the total time-interval with the length of each cycle, $T/A$. So the system utility function is thus obtained by summing up the utility of the all the individual cycles until $T/A$.

To find the best strategy of collaboration between the partners (human and robot), the goal is to maximize the expected utility, which is:

$$\frac{T}{A}\left((1+c)F(A) - c\right) \qquad \textbf{Equation 6.21}$$

### 6.5.4. Timing-based control model

We assume the human total time has a normal distribution with mean 70 (mean data collected from Jointec AB website[4]) and standard deviation 5. For an 8 hour work shift, $T$ is calculated as 8 x 60 x 60 = 28,800. Assuming a cost of 5 units (in other words, let's say for every defective pallet 5$ is to be calculated as loss incurred and for each perfect pallet the company earns a profit of 1$), when the expected utility is maximized as represented by equation – 6.20 above. Figure 6.7 and Figure 6.8 indicate the system behavior.

[4] www.jointec.se

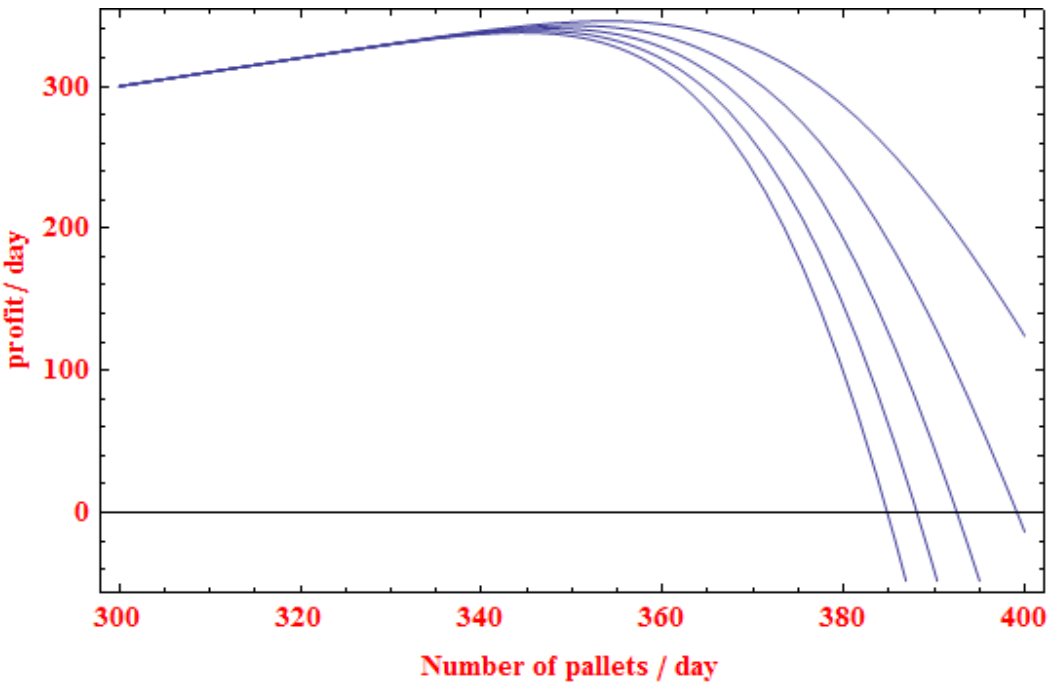



**Figure 6.7 Number of cycles *(T/A)* vs. the profit for a H-R system with system cost varying from 1 to 5**

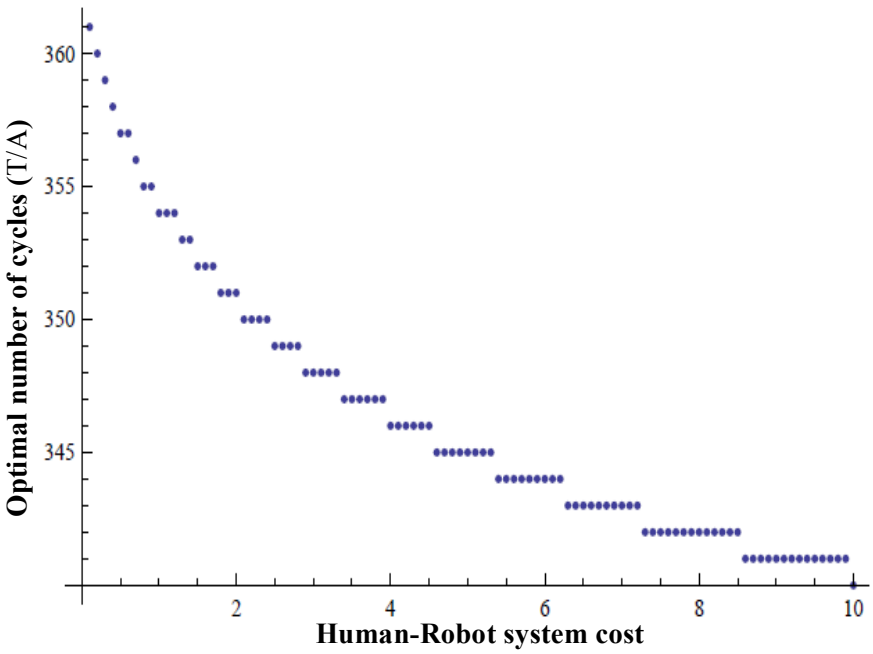



**Figure 6.8 Optimal number of cycles *(T/A)* vs. H-R system cost to ensure optimal productivity**

Next, we analyze how the variable *T/A* (the total number of cycles) gets affected when the cost is varied from 0 to 10. The graph above shows the system behavior. The figure indicates that as the H-R system cost increases by 10 folds, the total number of pallets that can be produced decreases by nearly 4%, as expected. To avoid the possibility of human error, the cycle time must increase so that the human operator receives ample amount of time to finish his task and cross-check for error. As cycle time increases, the total number of cycles *(T/A)* offering optimal productivity keeps decreasing steadily.

### 6.5.5. Adaptive control model

Assume that the human preparation time for pallet $\#i$ is normally distributed with a known mean $\mu_i$ and known standard deviation $\sigma$. T

he question to be asked now, if the robot can be programmed with adaptive control (a different length for each cycle), what are the optimal lengths of the cycles. Mathematically, the optimization problem has two stages. In the first stage, the number of cycles *(n)* should be determined. In the second stage, the robot inter-visits times ($A_1,\ldots,A_n$) should be determined. It should be noted that $\sum_{i=1}^{n} A_i = T$ means that the total time of robot action is a working day. The second stage is as follows. For any *n*, one needs to solve the optimization problem,

$$\underset{A_1,\ldots,A_n}{Max} \sum_{i=1}^{n} (1+c)\left(\Pr\left(X_i < A_i\right) - c\right) \quad s.t. \sum_{i=1}^{n} A_i = T \qquad \textbf{Equation 6.22}$$

We recall that, $\Pr\left(X_i < A_i\right) = \Phi\left(\frac{A_i - \mu_i}{\sigma}\right)$.

We apply the method of Lagrange multipliers as follows. This method formulates the constraint in the form $g\left(A_1,\ldots A_n\right) = 0$ and the whole problem is formulated as,

$$\underset{A_1,\ldots,A_n}{Max}\ f\left(A_1,\ldots A_n\right) \quad s.t.\ g\left(A_1,\ldots A_n\right) = 0 \qquad \textbf{Equation 6.23}$$

Then we seek for $A_1,\ldots A_n$ and $\lambda$ (called the Lagrange multipliers) such that for all $i = 1,\ldots,n$ we have,

$$\frac{\partial}{\partial A_i} f(A_1,...A_n) = \lambda \frac{\partial}{\partial A_i} g(A_1,...A_n) \qquad \textbf{Equation 6.24}$$

And, $g(A_1,...A_n) = 0$.

In our case the problem is,

$$\underset{A_1,...,A_n}{Max}\ (1+c)\sum_{i=1}^{n} \Phi\left(\frac{A_i - \mu_i}{\sigma}\right) \quad s.t. \sum_{i=1}^{n} A_i = T \qquad \textbf{Equation 6.25}$$

We can see that in our problem the function are additive in the variables, and hence the equations to be solved are,

$$(1+c)\Phi'\left(\frac{A_i - \mu_i}{\sigma}\right) = \lambda \qquad \textbf{Equation 6.26}$$

Recall that, from $\Phi'(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$ we get that $A_i - \mu_i$ is a constant. The constant (denoted by $a$) is determined by the constraint, $na = \sum_{i=1}^{n}(A_i - \mu_i) = T - \sum_{i=1}^{n}\mu_i$ and therefore,

$$a = \frac{T - \sum_{i=1}^{n}\mu_i}{n} \qquad \textbf{Equation 6.27}$$

$$A_i = a + \mu_i \qquad \textbf{Equation 6.28}$$

In this way, we can calculate the optimal length of each adaptive cycle ($A_i$) and the total number of H-R interaction cycles ($n$) possible in the given time period ($T$) to complete the task of pallet manufacturing. Since one pallet is produced in every H-R interaction cycle, the total number of possible H-R interaction cycles ($n$) also indicates the maximum number of pallets that can be produced using the adaptive control model.

# Part B – Simulation Study

Complex collaborative scenarios (Table 6.2) were also investigated to study the effect of influencing parameters, like user-proficiency (novice/expert), system reliability variables (e.g., sensor data accuracy, mechanical constraints), for different coordination protocols and control models. Analytical analyses of the effect of these factors are computationally intensive and complex by nature. Therefore, a simulation model of the same H-R system was developed and four complex case studies were analyzed.

## 6.6. Methodology

The simulation model was developed in Matlab and system analysis was performed by employing the Monte Carlo method. For the given user-proficiency level, system reliability, coordination protocol and control model, the behavior of the H-R system was studied based on 1000x1000 iterations of simulated H-R handovers. The values of each of the variables (Robot total time, RTT and Human total time, HTT) were randomly sampled each time to compute the results. Four case-studies were analyzed for which effective coordination strategies were derived.

### 6.6.1. Investigated influencing parameters

Two influencing parameters were evaluated, user-proficiency (novice/expert) and system reliability for different coordination protocols and control models. User proficiency was modelled by variability in user's time of arrival at the point of handover (novice – high variability; expert - consistent average arrival times). The system reliability variable takes into account the various factors that affect sensor data accuracy and mechanical constraints.

User-proficiency and system reliability were expressed as the HSD (human standard deviation) and the RSD (robot standard deviation) for the human total time (HTT) and robot total time (RTT). HSD will be larger if the human is a novice and smaller for an expert. Similarly, a robot with low mechanical constraints will have a lower RSD and a robot with unreliable sensors will have greater variance. When an averagely trained human works with the robot, we still consider differences in HSD. This is because the level of preparedness or the skill set of the human directly influence the human's perceptual latency, temporal preparation etc., which influence coordination in a collaborative task.

### 6.6.2. Control model implementation

It is assumed that the mean time required for the human and the robot individually to complete one cycle of the given collaborative task is T seconds. The robot and the human repeat the pre-defined set of actions every T seconds. Thus the H-R interaction at the spatial point of handover should ideally occur every T seconds. The two variables, HSD and RSD, were assigned with different values to simulate scenarios with novice/expert user-proficiency and similarly scenarios with reliable/unreliable sensors and low/high mechanical constraints. The cost of waiting at the point of handover W, for the human is calculated as, $W = R(t) - H(t)$, where, R(t) and H(t) are the times taken by the robot and human respectively to complete one round of action. The scenario was simulated for RTT (Robot Total Time) and HTT (Human Total Time) with mean values of T=30 seconds. By applying the Monte Carlo method, each of the scenarios was simulated for $10^6$ iterations for each combination of HSD and RSD. The values of RTT and HTT were randomly sampled in each simulation. Results indicate the average human waiting cost for $10^6$ iterations under different scenarios.

## 6.7. Simulation analysis of timing-based control model of H-R system

### Case-study III

Assume a collaborative scenario where the human proficiency level is that of an expert with low variance, HSD=1, and the robot has some inherent mechanical constraint that causes some variance in its motion so that, RSD=3. The coordination protocol 1 was implemented between the partners, i.e., whoever arrive first waits for the other. Figure 6.9 shows the average human cost of waiting (W) for a simulation with these scenario settings, using the aforementioned cost equation, averaged over $10^6$ times of operation (total number of collaborative events in the simulation model), and plotted against the HTT, the total human time required for completing one round of action. The human cost of waiting is lower when HTT of the collaborating human is greater than its mean value. Overall, the cost is lower for HTT values in the range between 27 and 35 sec. So, the bounded range between -10% and +17% of mean cycle time can be considered as the best zone or “critical zone” of collaboration for the given context.

**Table 6.2 Case-studies for simulation analyses of H-R system**

| Case-Study | Analysis Method | Control Model | Co-ordination Protocol | User-Proficiency |
|---|---|---|---|---|
| III | Simulation | Timing | Protocol 1 | Novice / Expert |
| IV | Simulation | Timing | Protocol 2 | Novice / Expert |
| V | Simulation | Sensor | Protocol 1 | Novice / Expert |
| VI | Simulation | Sensor | Protocol 2 | Novice / Expert |

The current collaborative task can have a higher level of team-coordination if the human completes the task in between 27 and 35 sec in every handover cycle.

Similarly, the coordination will be worse when the human is operating in the range between 24 and 27 sec, with the cost reaching its maximum when time taken by the human to complete one round of action is about 26 sec. When completing the action faster than required, humans may feel that they raise the productivity of the collaborative task, but actually team coordination suffers, and the throughput of the collaborative task decreases. Better team-coordination is achieved in such scenarios for the region where HTT is greater than its mean value. A higher value of RSD is representative of a robot with lower accuracy, and an HTT greater than its mean value signifies a slow user. Hence, it can be derived that *it is always better for a user to work slowly with an inaccurate robot*.

When the variance of both collaborating partners decreases (as with expert users and fairly accurate robots), better coordination is possible for the region where HTT is closer to its mean value. As it can be expected that an expert user will have better consistency in its arrival time, the region closer to the mean value is representative of the temporal behaviour of such users. So, the *effective coordination strategy between an expert user and a fairly accurate robot would be to maintain consistency*.

### Case-study IV

Coordination protocol 2 was implemented in this simulation. In this case, if the handover is not successful in the first attempt, the human waits for the return of the robot to repeat the action. If missed handovers happen consecutively, the coordination protocol may generate significant system costs, along with an inherent cumulative error in the process, causing the

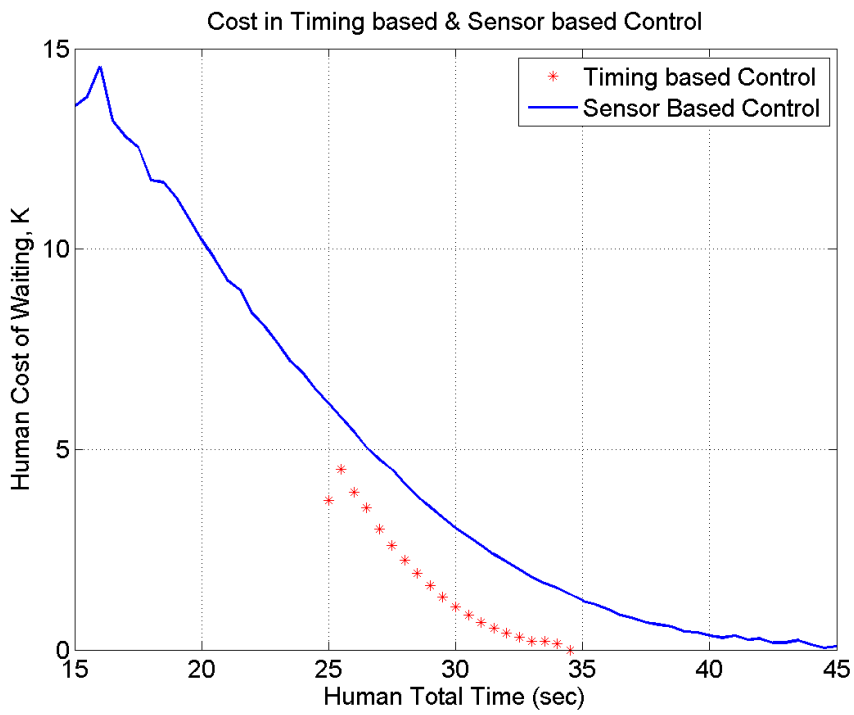



**Figure 6.9 Case-study III and V: Average human waiting cost for 1000x1000 H-R handover cycles with timing-based control (dotted red line) and sensor-based control (bold blue line)**

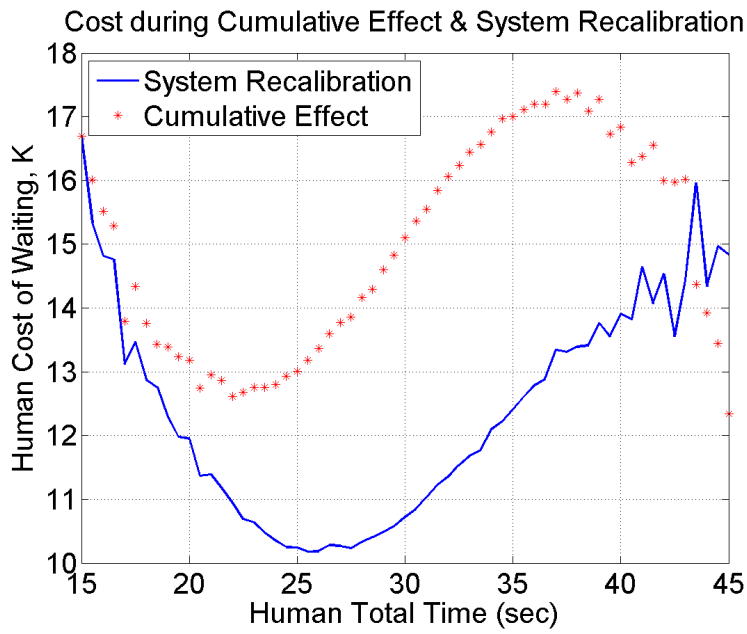



**Figure 6.10 Case-study IV and VI: The cost curve for the collaborative system with cumulative effect (*dotted line*) and with system recalibration (*blue line*)**

collaborative process to become completely arrhythmic. A cumulative error arises in the process because in this coordination protocol, the success or failure of the handover in the previous handover cycle may have an effect on the current one. This scenario was simulated for HSD=4 and RSD=8 and the cost curve is represented by the red dotted line in Figure 6.10.

The HTT within the range 15-20 sec is basically the region when the human proactively attempts to arrive at the point of handover before the robot. In the range between 35 and 40 sec, the human arrives in most cases late and hence misses the first handover, having to wait for the second turn and adding a cumulative cost to the process. If the human arrives too early, the cost is higher than the optimum value, but it is always lower than the cost of handover in the second turn. *If a system does not have the ability/possibility to recalibrate itself, it is always better (for the human) to maintain a tendency to arrive earlier, before the robot* (to be on the lower side of the mean). However, the best zone of collaboration, offering most effective team-coordination, is in the region between 20 and 25 sec for the scenario represented by the cost curve in dotted lines. It should be noted that this region was considered as the worst zone of collaboration in the cost curve of Case-Study III. This implies that *H-R effective coordination strategy must be context specific*.

## 6.8. Simulation analysis of sensor-based control model of H-R system

### Case-study V

A simulation model of the H-R system was developed for the sensor-based control model, using coordination protocol 1 (as in case-study III). The robot´s action in this case depends on the information it received from its sensors that sense the state of the human and the robot. An average human was modelled with HSD=4. In the simulation, the robot has low quality sensors, and consequently the variance of the robot total time, RTT, is high with RSD = 8.

This scenario was simulated, and the average human waiting cost was calculated for $10^6$ iterations, as shown by the blue continuous line in Figure 6.9. The graph clearly shows that the system cost in this case is much higher than case-study III as represented by the dotted line. So, in such a scenario, the best collaboration is in the range of 33-40 sec (higher than the mean value) and the cost increases as the human total time drops beneath its mean

value. *This implies that when the robot has an unpredictable motion, it is always better to collaborate as slowly as possible to improve team-coordination.*

### Case-study VI

In this case-study, the previous case-study IV was simulated with the robot equipped with the ability to sense and recalibrate itself whenever it crosses a certain threshold value of human waiting time. This threshold value can be defined as the maximum time allowed for a single event of H-R handover to be executed. If such functionality is added to the H-R system, team-coordination can be drastically improved. Such a scenario was simulated for the same value of parameters (HSD=4, RSD=8), and we plotted the result with the bold continuous line (in blue), as shown in Figure 6.10. Clearly the cost of such a system is much lower than the previous case for a wider range of values.

The best zone of collaboration in this case is between 22 and 31 sec, a rather broad range. Normally, a novice user collaborating with the system can have a higher chance of arrhythmic or unpredictable movement. Such a broad range defined as the best zone of collaboration is essentially suitable for such user groups collaborating with the system. Thus, *a novice user can maintain adequate H-R team coordination if the system has the ability to recalibrate itself.*

## 6.9. Comparative analysis of analytical and simulation study of H-R system

A comparative analysis of analytical and simulation study of H-R system was done for case-study I. Results (Figure 6.11) show that the overall behavior of the system remains the same and point to the same conclusions. Figure 6.11a shows the average system cost against constant robot cycle time, A. For a given robot cycle time (A), the system cost was computed for each H-R handover cycle and averaged over $10^4$ cycles of H-R collaboration. The graph shows the characteristics of the system as the robot cycle time increases from 0.5 to 1.2. The five plots show the characteristics of the system when the cost of human waiting per unit time, $C_h$ increases from 0.5 (the bottom line shown in black) to 5.5(the top line shown in magenta).

It indicates that the system cost is lowest when A equals 1 for $C_h$ varying between 0.5 and 2.5. Thereafter, as $C_h$ further increases in value, the system cost is lowest for A=0.5. This behavior points to the same two conclusions as obtained from analytical study, namely:

a) For certain range of values of $C_h$, the value of optimal A remains constant.

b) Outside this range, the change in the optimal value of A occurs in steps (from A=1 to A=0.5)

Figure 6.11 indicates the average system cost when $C_h$ increases from 0 to 200. The behavior of the system remains the same as in the case of analytical study (Figure 6.2). It should however be noted that for the simulation study, average system cost was computed instead of optimal system cost as done in the analytical study. This is because, in the simulation study, the system cost is computed through simulations of all the possibilities.

## 6.10. Comparative analysis of timing- and sensor-based control models

### 6.10.1. Functional comparison of timing- and sensor-based control model (Case-study III and V)

Figure 6.9 shows the cost-curve for case-study III (timing-based control model) and V (sensor-based control model) for coordination protocol 1. Results indicate that the system cost is very high in sensor-based control. *So, timing-based control model could be a better option than sensor-based control for a system with unreliable or inferior quality sensors*.

### 6.10.2. Comparison of timing- and sensor-based control model for novice users (Case-study III & V)

In Figure 6.9, the HTT region spanning 15-45 sec is where the novice user mostly operates, with some being too early (15-20 sec) or too late (35-45 sec) and some fluctuating between the two extremes.

The results of case-study V (Figure 6.9) indicate that a sensor-based control model, equipped with unreliable and/or inferior sensors can be problematic for a novice user, because the cost of waiting (the blue line in the figure) for a novice user with a tendency to work at a faster pace can be maximum (the area marked with a red ellipse). If it is compared to the average cost for an expert user in the sensor-based model (as indicated by the horizontal red arrow), the cost varies only between 13 to 40% of the maximum value. This is the average waiting cost that will exist even during the timing-based control. High waiting cost implies that the user's average waiting time for each round of collaboration can be quite high.

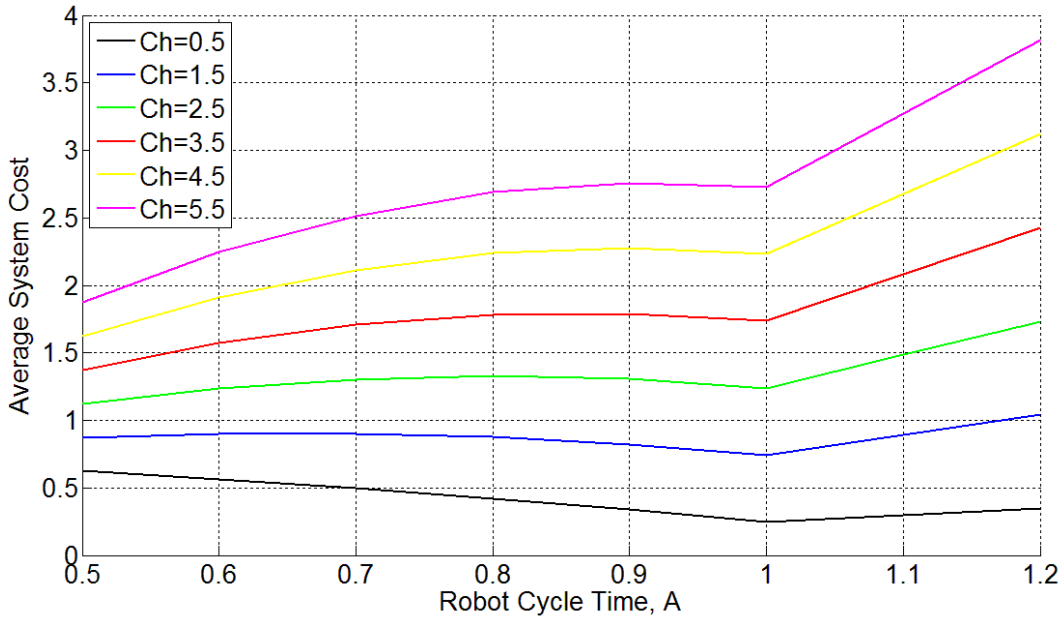



**Figure 6.11 Simulation analysis of the case-study I - average system cost against a constant robot cycle time, *A***

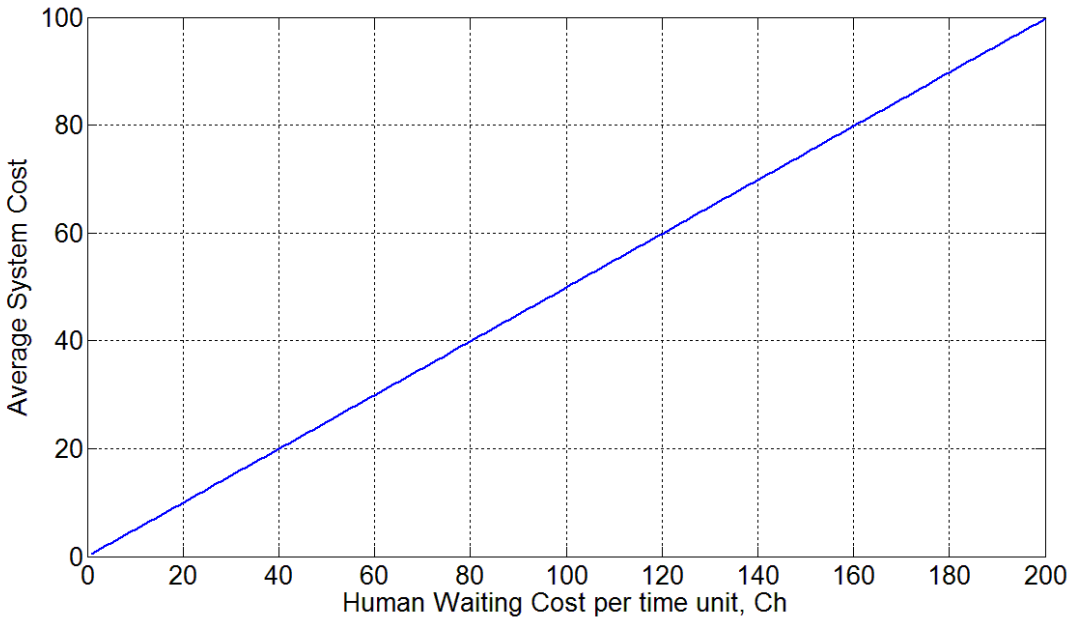



**Figure 6.12 Simulation analysis of the case-study I - average system cost against human waiting cost per unit time, $C_H$**

This will directly affect the H-R coordination and the productivity of the system. With lack of coordination, it is also difficult for a user to develop a natural rhythm in synchronization with the robot partner resulting in poor user-experience in sensor-based control. In these cases, a timing-based control model can help the novice user. With it, the user can develop a natural rhythm, synchronized with the robot's predictable fixed rhythm. Such user behaviour is in line with research in psychology, which shows evidence that humans have a natural tendency to adapt to an external rhythm (Keyfitz and McNeill 1996; Lorenz et al. 2015).

A recent study has also shown that human adaptation in a human-robot system can significantly improve team collaboration (Nikolaidis et al. 2016). In contrast, with the sensor-based control model, the robot follows the user, and the user will have greater difficulty developing a synchronized rhythm. When the user arrives with a long delay, irrespective of the control model used, the robot will be ready for handover (waiting cost close to zero). This, however, is not an efficient solution, as the long waiting time for the robot means lower throughput and will add to unnecessary unproductivity costs.

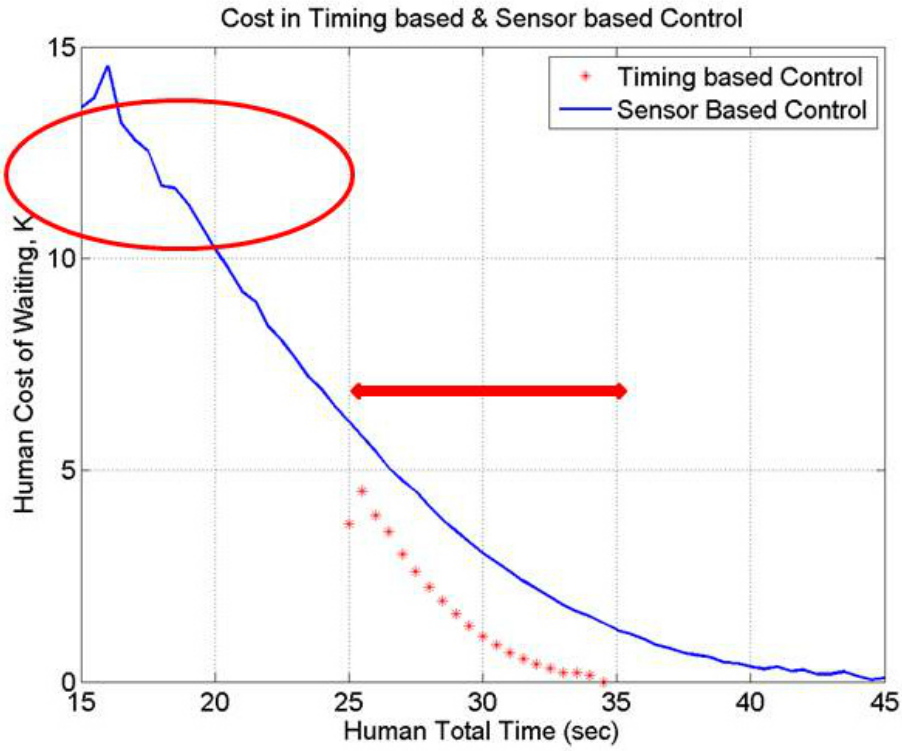



**Figure 6.13 Timing based model suits better for Novice Users whereas Sensor based model is most appropriate for expert user**

### 6.10.3. Comparison of timing- and sensor-based control model for expert users (Case-study III and V)

An expert user profile, for the investigated scenario, is characterized by a human with small variation and better consistency in the average time of arrival at the point of handover. As such, the HTT region closer to the mean value (Figure 6.9) is a representative of the temporal behavior of such a user group. The area marked by the broad horizontal red arrow (for HTT values ranging between 27 and 35 sec) has been considered as the operational zone for expert user profile in this study. Figure 6.9 indicates that both control models fare equally well for expert users. The waiting cost in either of the cases follows the same trend and hardly has any significant difference. As can be seen in the figure, the cost in either of the control models varies between 13 to 40% of the maximum cost in sensor-based control in this region.

This is logical, because an expert user will take more or less the same amount of time to accomplish each cycle of tasks. As a result, it can be assumed that an expert user has already developed a natural rhythm for the collaborative task. As discussed in the previous section, a timing-based control model is suitable for rhythmic interaction; it is now self-explanatory why waiting cost is lower for expert users in timing-based control model.

The sensor-based control model, too, has a low waiting cost for expert users, because in this case the user remains always predictable. Since the user already has an inbuilt rhythm for the task, this control model does not introduce any discontinuity into the system, as is the case for a novice user using a sensor-based model. Instead of making the trained user follow a fixed robot rhythm, the sensor-based control assists such users to continue at a pace that is appropriate for them.

Even though both models fare equally for an expert user, a sensor-based control model is better for such users, because it can offer greater flexibility. Moreover, fatigue effects may slow the user over time and may lead to changes in performance. In this case, a sensor-based model would give a feeling of an ideal companion as a co-worker that adapts itself to the changing pace of the partner. Another possibility for an expert user is to have a hybrid control system, offering both options. Timing-based control, in that case, can initially be used for the collaborative task, and sensor-based control can be used after task performance has become consistent. Thereby the benefits from both control systems can be reaped.

## 6.11. Discussion of Analytical and Simulation Study

Table 6.3 below summarizes the six case-studies on H-R collaboration investigated using analytical and simulation methods. Based on this study, it can be said that depending upon the user's proficiency level, the system reliability and the coordination protocols used for a given task, different coordination strategies can be employed to improve temporal fluency in team coordination and overall system productivity. The effective coordination strategy for human in different scenarios is presented in Table 6.3. These strategies are user-centric and aim at improving the team fluency and system productivity.

The analytical and simulation analyses methodology presented in this chapter can be used to:

- predict the level of team-coordination between the partners and hence performance of human-robot collaboration as a team for a given repetitive task;
- study the behaviour of the system when the influencing parameters are tuned thereby predicting the preferable (and when possible optimal) way to collaborate for dynamic scenarios;
- develop a system objective function which can be employed as a general design tool to measure H-R system performance.

**Table 6.3. Suggested Human Coordination Strategy for Different Scenarios**

| Case-Study | Control Model | Co-ordination Protocol | User-Proficiency | Robot Characteristics | System Recalibration | Suggested Coordination Strategy for Human |
|---|---|---|---|---|---|---|
| I | Timing | Protocol 2 | Novice | Accurate | Not investigated | Avoid any deliberate delay. |
| II | Timing | Protocol 2 | Expert | Accurate | Not investigated | Avoid any deliberate delay |
| III | Timing | Protocol 1 | Novice | Fairly Accurate | N/A | Work slower than robot mean cycle time |
| | | | Expert | Fairly Accurate | N/A | Maintain consistency around robot mean cycle time |
| IV | Timing | Protocol 2 | Novice / Expert | Unpredictable | Without Recalibration | Work faster than robot mean cycle time |
| V | Sensor | Protocol 1 | Novice | Unpredictable | N/A | Work slower than robot mean cycle time |
| | | | Expert | Unpredictable | N/A | Work slower than robot mean cycle time maintaining consistency around +20% of robot mean cycle time |
| VI | Sensor | Protocol 2 | Novice | Unpredictable | With Recalibration | Avoid being too fast or too slow |
| | | | Expert | Unpredictable | With Recalibration | Work faster than robot mean cycle time maintaining consistency around -20% of robot mean cycle time |

N/A = System Recalibration is not applicable for Protocol 1

# Chapter 7 | Experimental Study of H-R Collaboration Models

***Chapter Overview***

This chapter presents the experimental studies of the human-robot collaboration models presented in chapter 5. The models were implemented in an integrated Human-Robot operational system involving a time-critical joint handover task in a shared work, time-space.

Three experiments with 200 subjects in total were conducted to validate, evaluate and compare the models for a wide range of collaborative tasks with varying degrees of complexity in terms of cognitive and time-demand. The first experiment analyzed H-R collaboration in long and simple tasks [BGU final project, Sayfeld and Peretz 2014]; the second and third experiments analyzed a short-cycle and simple task and a long and complex task respectively [BGU final project, Moyal and Goldshtein, 2015]. The chapter is structured into three main sections where each of these experiments is discussed in detail.

## 7.1. Methods

### 7.1.1. Overview

An integrated human-robot collaborative work cell was designed for the experiments. Three separate experiments with 200 subjects in total were carried out for three types of collaborative tasks respectively, as detailed in Table 7.1 below (Sayfeld and Peretz 2014; Moyal and Goldshtein 2015). The tasks had varying degrees of complexity in terms of cognitive and time-demand, namely – Short and Simple Task, Long and Simple Task, Long and Complex Task. Four performance measures were analyzed – (i) Total assembly time (ii) Total idle time distribution (iii) Rate of successful handovers (iv) Subjects' preferences for working with the three models (only for Exp. 1).

Subjects were asked to do a given task three times with a break of 5 minutes between sessions. In each of these sessions, subjects worked with the robot with a different randomly chosen H-R collaboration model (timing, sensor and adaptive) to accomplish the given task.

All the experiments were officially approved by the University's Human Subject Research Ethics Committee.

**Table 7.1 The three experiments on H-R team-work**

| Experiment | Title |
|---|---|
| Experiment I | HRC for Long and Simple Task |
| Experiment II | HRC for Short and Simple Task |
| Experiment III | HRC for Long and Complex Task |

### 7.1.2. The system

The system Figure 7.1 consisted of a five degree of freedom revolute robotic arm (Scorbot ER4U) mounted on a table top with an area dedicated to human-robot interaction and two other areas dedicated towards primary and secondary (if applicable) tasks of the robot respectively.

### 7.1.3. Participants

80 subjects participated in Experiments I and II and 40 subjects participated in Experiment III. The subjects consisted of undergraduate students from the University aged 21-27 years. Each subject spent about 30 minutes working with the H-R system. As the subjects entered the experimental arena, they were briefed about the H-R system, the given collaborative task, the primary and secondary task of the robot and of the human (in this case, the subject). There was no secondary task for the robot in Exp. II as it was a short-cycle task requiring frequent interaction.

Of the total subjects, half of them were informed about the working principle of the three models and half of them were only aware that they are supposed to work with three different models in each of the three sessions they executed the task. Subjects were video recorded with their consent. The subjects received a score of 1 point towards an undergraduate course in Automation Engineering as an incentive for investing their time in the experiment.

### 7.1.4. Performance measures

Three performance measures of fluency of a collaborative task were recorded and analyzed – total assembly time (human and robot together), total idle time, rate of successful handover. Experiment I also includes subjective measures – subjects were asked to fill-out

a questionnaire for subjective assessment of the system, the collaborative task and their experience of working with each of the three models.

### 7.1.5. Data analysis

Data analysis was done separately for each of the three experiments using SPSS and included the following steps:

1) Outlier removal

2) One-way ANOVA with block was done on the idle time distribution and total assembly time for each of the three models. The block represented the subjects and the goal was to check if there was any effect of the subjects on the results.

3) Two hypotheses were formed for ANOVA analysis:

**Hypothesis 1**

$$H_0: \mu_1 = \mu_2 = \mu_3$$

There is no significant difference between the models

$$H_1: \mu_j$$

At least one of the models is different from the other

**Hypothesis 2**

$$H_0: \sigma^2{}_{Block} = 0$$

There is no significant difference between the subjects

$$H_1: \sigma^2{}_{Block} > 0$$

There is significant difference between the subjects

4) Following a one-way ANOVA analysis with block, if the null hypothesis remains valid, i.e., there is no statistically significant difference between the subjects, then the block was ignored and the first hypothesis was re-evaluated using one-way ANOVA without block.

5) Following the ANOVA analysis (with or without block depending upon the results), post-hoc analysis using the LSD / HSD method for multiple comparisons was performed. Results of the analysis have been abbreviated by using **T** for timing-, **S** for sensor- and **A** for adaptive control model.

Three hypotheses were formed for this analysis:

**Hypothesis 1**

$$H_0: \mu_{timing} - \mu_{sensor} = 0$$

Timing model is not significantly different from the sensor model

$$H_1: \mu_{timing} - \mu_{sensor} \neq 0$$

Timing model is significantly different from the sensor model

**Hypothesis 2**

$$H_0: \mu_{timing} - \mu_{adaptive} = 0$$

Timing model is not significantly different from the adaptive model

$$H_1: \mu_{timing} - \mu_{adaptive} \neq 0$$

Timing model is significantly different from the adaptive model

**Hypothesis 3**

$$H_0: \mu_{adaptive} - \mu_{sensor} = 0$$

Adaptive model is not significantly different from the sensor model

$$H_1: \mu_{timing} - \mu_{sensor} \neq 0$$

Adaptive model is significantly different from the sensor model

6) Following the analysis of idle time distribution and total assembly time, logistic regression was performed on the data relating to the rate of successful handovers to check for any significant difference between the models.

7) The effect of human learning curve on the models was checked by computing the Spearman's correlation coefficient. The possible learning effect during each model was assessed from the slope of the graph between the number of rounds of H-R handover cycles and the respective assembly time for that particular round.

## 7.2. Experimental hypotheses

The objective of the experimental study was to analyze the performance of the three control models for different types of tasks differing in length and complexity. The following hypotheses were investigated through three experiments.

For Human-Robot collaborative team work:

*Hypothesis 1:* Timing control model is best suited for short-cycle and simple tasks.

*Hypothesis 2:* Sensor control model is best suited for long and simple tasks.

*Hypothesis 3:* Adaptive control model is best suited for long and complex tasks.

## 7.3. Experiment I – Long and simple task

### 7.3.1. The task

In this experiment (Figure 7.1) the collaborative task is to build a tower using Lego blocks. The robot delivers these blocks to the human through human-robot handovers involving direct HRI. The primary task of the human is to fix the building blocks on to the tower platform.

The secondary task of the human is to fix 20 pins around the periphery of the tower for each level. The human is supplied with a box of pins from which the subject may pick only one at a time. The box has a proximity sensor which tracks the number of pins picked up by the human over time. The human can move to the next floor level only after these 20 pins are mounted. In between each human-robot handover cycle, the robot has a secondary task of filling-up the buffer of Lego blocks to be used in the primary task. Unlike the secondary task of human, the robot may halt the on-going secondary task anytime and proceed with its primary task. This is to ensure that the robot remains at the disposal of the human as and when needed.

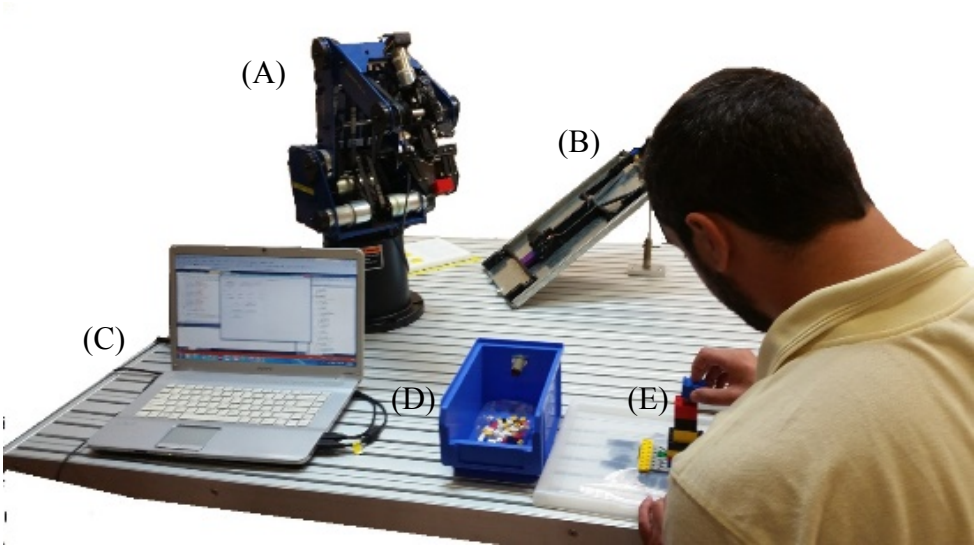



**Figure 7.1 The Human-Robot collaborative task in experiment I (A) the robot (B) the robot secondary task buffer (C) operating system (D) pins for human secondary task (E) assembly task**

The point of H-R handover is pre-defined so as to focus on the temporal aspect of HRI. Four H-R handover cycles were performed for each control model resulting in the completion of the given collaborative task (building of a tower for each model).

### 7.3.2. Implementation

The subject and the robot worked together in each of the three H-R collaboration models in the following way:

i. **Timing control model**: The robot delivers the necessary pieces for the tower at fixed intervals of time. The robot arrives at the pre-defined point of handover 70 seconds after the preceding handover.

ii. **Sensor control model**: The robot keeps track of the secondary task of the human (picking and placing 20 pins – one by one). When the human picks up the 13$^{th}$ pin, it triggers the robot to halt its on-going secondary task and initiate its preparation for the next H-R handover cycle. As a result, the robot switches its attention towards the primary task and picks up the piece and arrives at the point of handover X seconds after the received triggering signal.

iii. **Adaptive Model**: The robot anticipates the timing of the next handover cycle using three types of temporal cues/information: temporal data of the handover cycle of all the previous end-users; temporal data of the current end-user in all the previous handovers thus far; and the temporal data of the current end-user in the immediately preceding series of events. The latter is computed by checking the rate at which the subject picks up the three pins (11$^{th}$, 12$^{th}$ and 13$^{th}$) leading to the triggering signal (of the Sensor Model). The temporal prediction model for this experiment is represented by the following equation:

$$F = (20 - n)\{\alpha * D_T + \beta * D_S + \gamma * (\delta * P_n + \varepsilon * P_{n-1} + \ldots\ldots + \theta * P_{n-q})\}$$

**Equation 7.1**

where,

$F$ = the predicted value

$n$ = number of pins assembled

$D_T$ = general mean of population for assembly of one cube

$D_S$ = mean of the current human for assembly of one cube

$P_n$ = mean of assembly time for the-n cube

The initial values of the weights were calculated manually using the experimental data of a pilot experiment. The robot anticipated and accordingly adapted itself in time for each H-R handover cycle based on this equation.

### 7.3.3. Results

(a) **Total assembly time**: Analysis of the data relating to the total assembly time indicated the following:

i. There are significant differences (p=0.001) between the subjects ($H_0$ is rejected in the one-way ANOVA with block

ii. At least one of the models is significantly different (p=0.000) from the others.

iii. There is a significant difference (p=0.0001, p=0.002, respectively) between A & T and between A & S (Tukey HSD test).

The total assembly time for the adaptive model is significantly lower (p=0.002, p=0.0001) than the sensor control model and the timing control model by 7% and 14% respectively Figure 7.2. No significant difference (p=0.716) between the timing and the sensor control model was found.

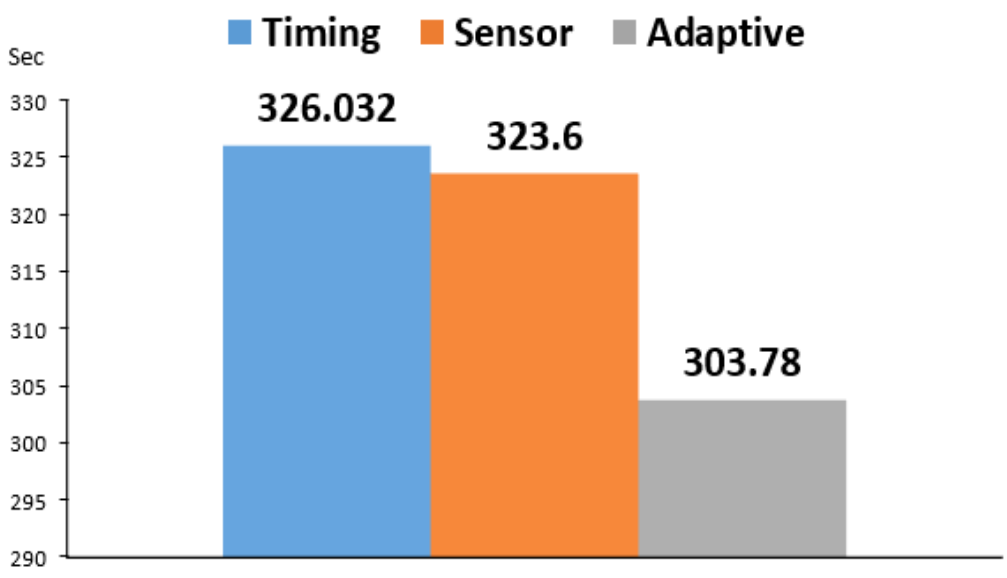



**Figure 7.2 The total assembly time in timing, sensor and adaptive model**

(b) **Total idle time**: Analysis of the data relating to the total idle time indicated the following:

i. There are no significant differences (p=0.192) between the subjects ($H_0$ is not rejected in the one-way ANOVA with block.

ii. At least one of the models is significantly different (p=0.001) from the others (re-evaluation using one-way ANOVA without block.

iii. There is a significant difference (p=0.0001, p=0.0001, p=0.002 respectively) between each of the models (T & S, A & T and A & S) (Tukey HSD test).

The total idle time for the adaptive model is significantly lower (p=0.002, p=0.0001) than the sensor control model and the timing control model by 60% and 39% respectively (Figure 7.3). The total idle time for the timing control model is significantly lower (p=0.0001) than the sensor control model by 35%.

(c) **Rate of successful handovers:** Figure 7.4 shows the rate of successful handovers for each of the control models.

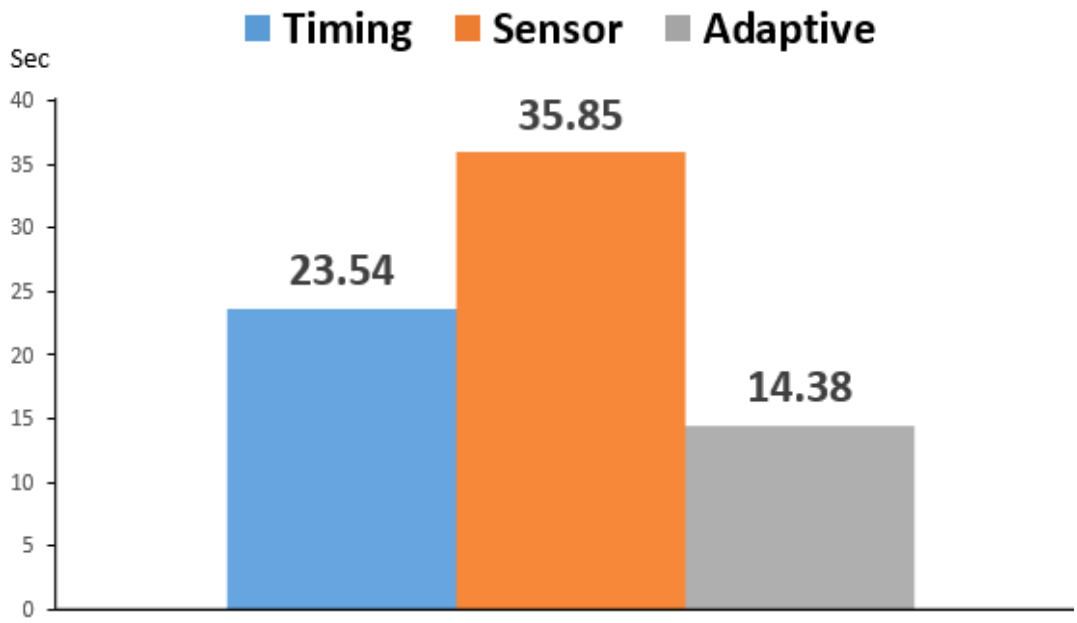



**Figure 7.3 The total idle time for timing, sensor and adaptive model**

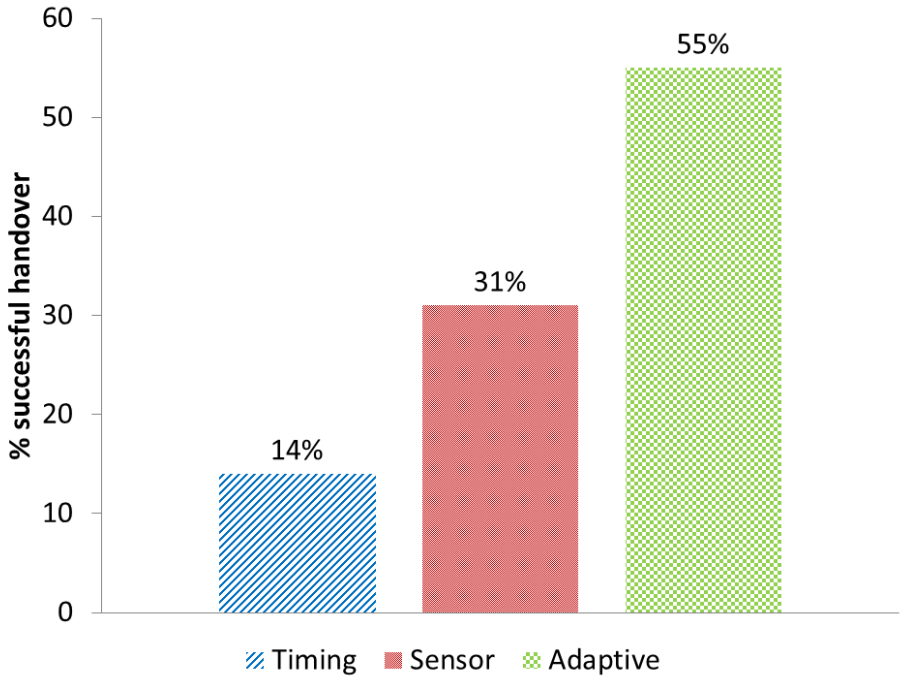



**Figure 7.4 Rate of successful handovers for timing, sensor and adaptive model**

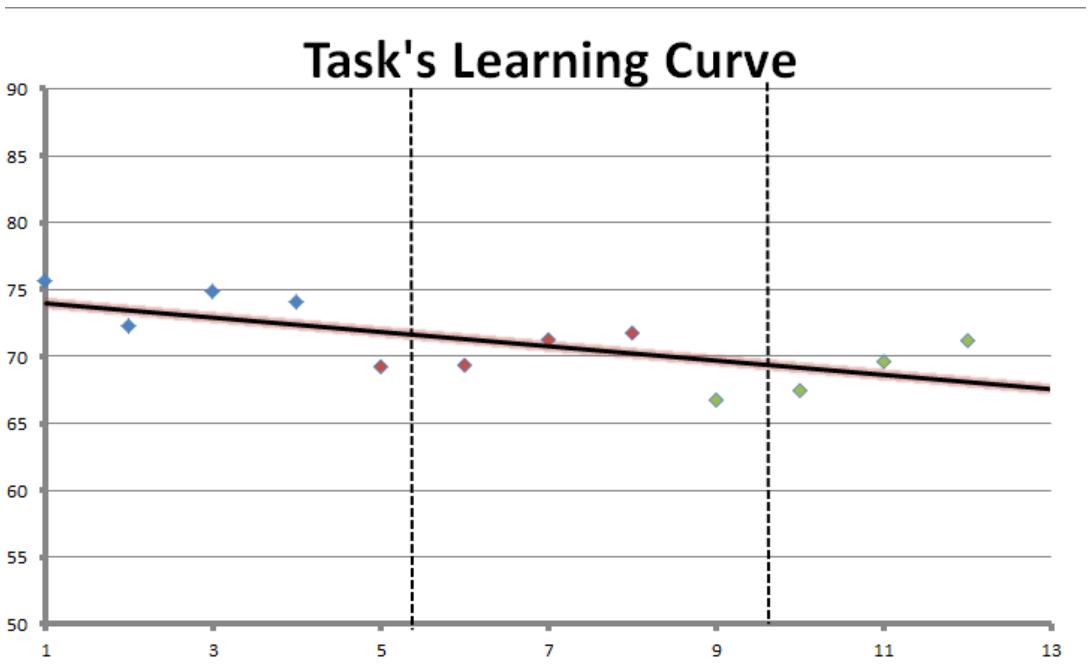



**Figure 7.5 Task learning curve (Sayfeld and Peretz, 2014)**

(d) **Task learning curve**: Figure 7.5 indicates a decrease in the total assembly time for building a tower implying human learning. This learning curve was expected during the design of the experiment and therefore a randomized sequence of models was selected to cancel the effect.

(e) **Subjective assessment of the H-R collaboration model**: Figure 7.6 shows the user-preference for the three control models following their working experience with the robot. Results indicate that the adaptive model was chosen by 45% of the subjects as the most preferred model for team-work followed by sensor model with 37%. Timing control model was the least preferred model with a user-preference of only 18%.

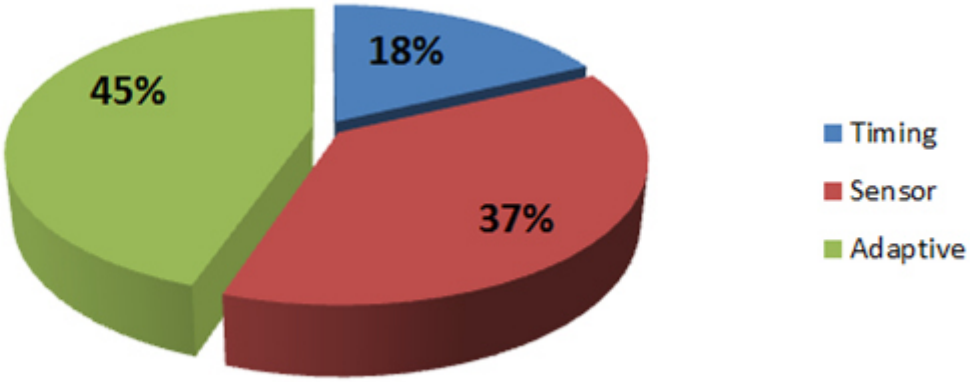



**Figure 7.6 Subjective assessment of the timing, sensor and adaptive model**

### 7.3.4. Discussion

Results show conclusively that there is a substantial decrease in total idle time (60% and 39% respectively) and significant reduction in total assembly time (7% and 14% respectively) for the adaptive model (best performing model) in comparison to the sensor- and timing control models. The adaptive model also had the highest rate (55%) of successful handovers which implies that the robot functional delay (Hoffman and Breazeal 2010) is the least in this model. The subjective measure of the user-preference for each of the control models also reveals that the adaptive model is the most preferred model for H-R collaboration. Based on these results, it can be said that ***adaptive model is best suited for long and simple tasks*** and the preliminary hypothesis that the sensor based model is best suited for this type of task is rejected.

## 7.4. Experiment II – Short and simple task

### 7.4.1. The task

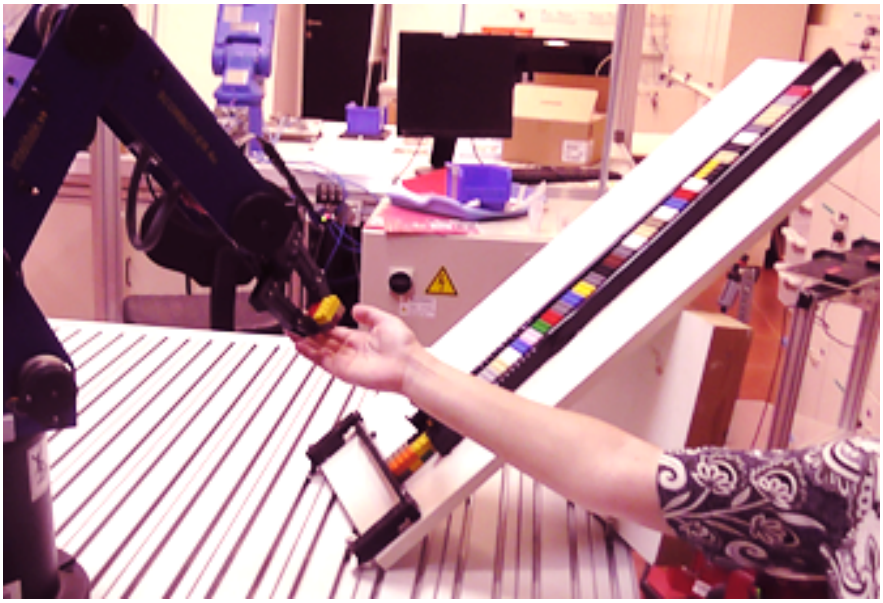
Since the interaction between human and robot is too frequent (less than 15 sec), the robot is assigned with no secondary task. The robot picks up a Lego block consisting of 4 small pieces of different colors – red, orange, blue, pink – and hands it over to the human. The human dismantles the four small pieces and performs the job of color sorting by putting the red piece in Box 1, black piece in Box 2 and the remaining two pieces (yellow and blue) in Box 3. This collaborative work goes on for 20 successive cycles with 20 H-R handovers.

The given task resembles a typical industrial task of manual inspection and sorting. Subjects were instructed to do the given task (20 H-R handover cycles of sorting) three times with intervals of 5 minutes between each session. In each session subjects worked with a different H-R collaboration model chosen randomly to accomplish the given task.

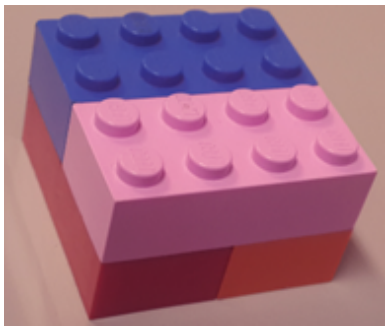
### 7.4.2. Implementation

The three H-R collaboration models were implemented in the following way:

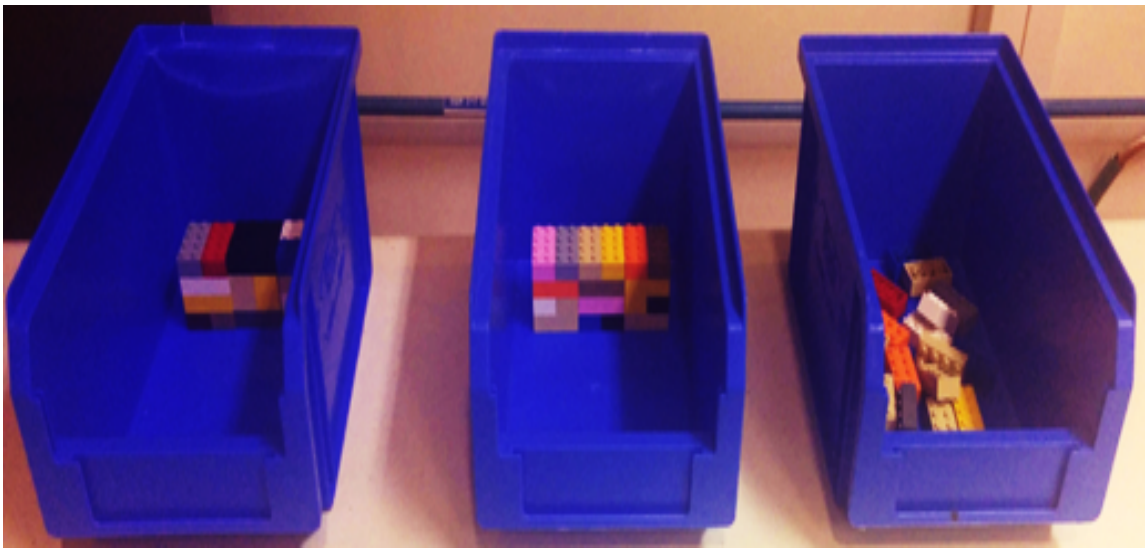
(Fig. 7.7a)



(Fig. 7.7b)



(Fig. 7.7c)



(Fig. 7.7d)

**Figure 7.7 The sequence of the Human-Robot collaborative task in Experiment II (a) the robot picks up a Lego block from parts warehouse (b) the robot-human handover (c) the Lego block that is being handed over (d) the human color sorting task**

i. **Timing control model**: The robot arrives at the pre-defined spatial point of handover (p-o-h) 10 sec after the conclusion of the last handover cycle. The robot continues this pre-defined repetitive action for 20 successive cycles.

ii. **Sensor control model**: The robot starts its action for the next cycle (i.e., picking up the subsequent Lego block from the assembly line) in reaction to the triggering signal it received about the state of the human work cycle. Of the three boxes (1, 2 and 3) where the human is supposed to place the dismantled (and sorted) pieces of Lego blocks in order, the one in the middle ($2^{nd}$ box) was equipped with a proximity sensor which sends a binary signal to the robot every time when the human drops the small pieces inside it thereby signaling the beginning of the preparations for the next handover cycle. The robot arrived at the p-o-h after 4 seconds from receiving this triggering signal.

iii. **Adaptive model**: The robot anticipates the timing of the next handover cycle using two types of temporal cues/information: temporal history of the preceding subjects and temporal history of the current subject in the last three handover cycles. Combining them, the temporal predictive model is represented by the following equation:

$$F = \alpha * D_T + \beta * (\gamma * P_n + \delta * P_{n-1} + \theta * P_{n-2}) \qquad \textbf{Equation 7.2}$$

where,

$F$ = the predicted value of the robot cycle time

$D_T$ = Mean time-period of the handover cycle of the population (all the subjects who has previously worked with the robot)

$n$ = number of the immediately preceding handover cycle of the current subject

$P_i$ = time-period of the current subject in the $i^{th}$ handover cycle

$\alpha, \beta, \gamma, \delta, \theta$ were calculated manually based on the pilot experiment data.

### 7.4.3. Results

(a) **Total assembly time**: Analysis of the data relating to the total assembly time indicated the following:

i. There are no significant differences (p=0.454) between the subjects ($H_0$ is not rejected in the one-way ANOVA with block.

ii. At least one of the models is significantly different (p=0.001) from the others (re-evaluation using the one-way ANOVA without block.

iii. There is a significant difference (p=0.001, p=0.001, p=0.001 respectively) between each of the models (T & S, A & T and A & S) (LSD test).

The total assembly time for the timing control model is significantly lower (p=0.001, p=0.001) than the sensor control model and the adaptive model by 30% and 10% respectively (Figure 7.8). The total assembly time for the adaptive model is significantly lower (p=0.001) than the sensor control model by 20%.

(b) **Total idle time:** Analysis of the data relating to the total idle time indicated the following:

i. There are no significant differences (p=0.261) between the subjects ($H_0$ is not rejected in the one-way ANOVA with block.

ii. At least one of the models is significantly different (p=0.001) from the others (re-evaluation using the one-way ANOVA without block.

iii. There is a significant difference (p=0.0001, p=0.0001 respectively) between T & S and A & S. (LSD test).

The total idle time for the adaptive model and the timing control model is significantly lower (p=0.001, p=0.001) than the sensor control model by 30% and 23% respectively (Figure 7.9). There is however, no significant difference (p=0.127) between the adaptive and timing control models.

(c) **Rate of successful handovers:** Logistic regression analyses indicated that the timing and sensor control models are significantly different (p=0.004, p=0.0001, respectively) from the adaptive model. The highest number of successful handovers (91%) is in the timing control model followed by the adaptive model with 80% success rate (Figure 7.10).

(d) **Task learning curve**: Figure 7.11 shows the task learning curve for the three models. Spearman's correlation coefficient was calculated for the data and it shows that there is a significant negative correlation ($\rho \sim -1$) between the models. This implies that the random sequential order of the model was not enough to cancel the effect of the learning curve. So, after removing the first 5 data points, Spearman's correlation coefficient was re-calculated resulting in $\rho \sim 0$, thereby indicating the cancellation of the learning effect.

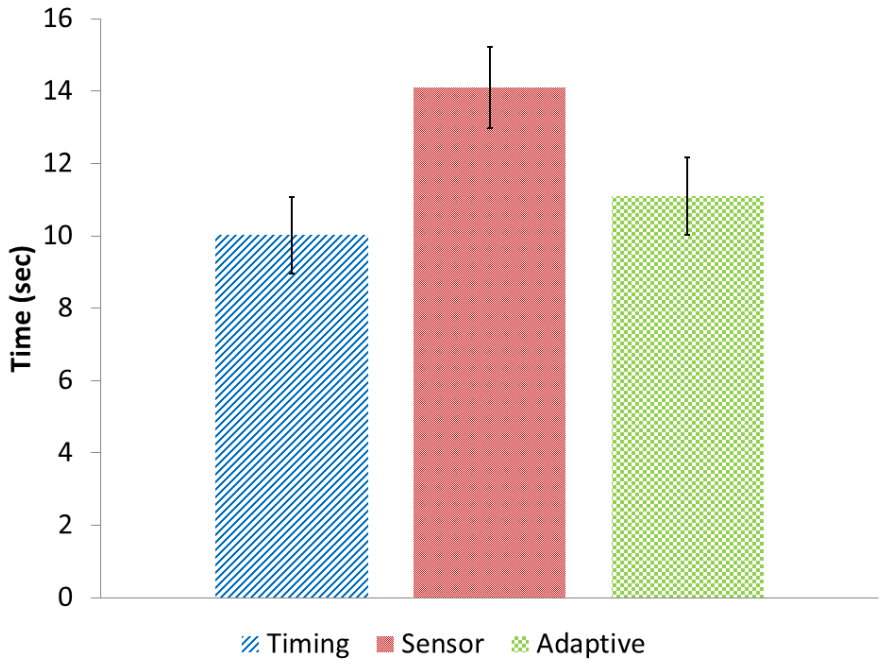



**Figure 7.8 The total assembly time for timing, sensor and adaptive model respectively**

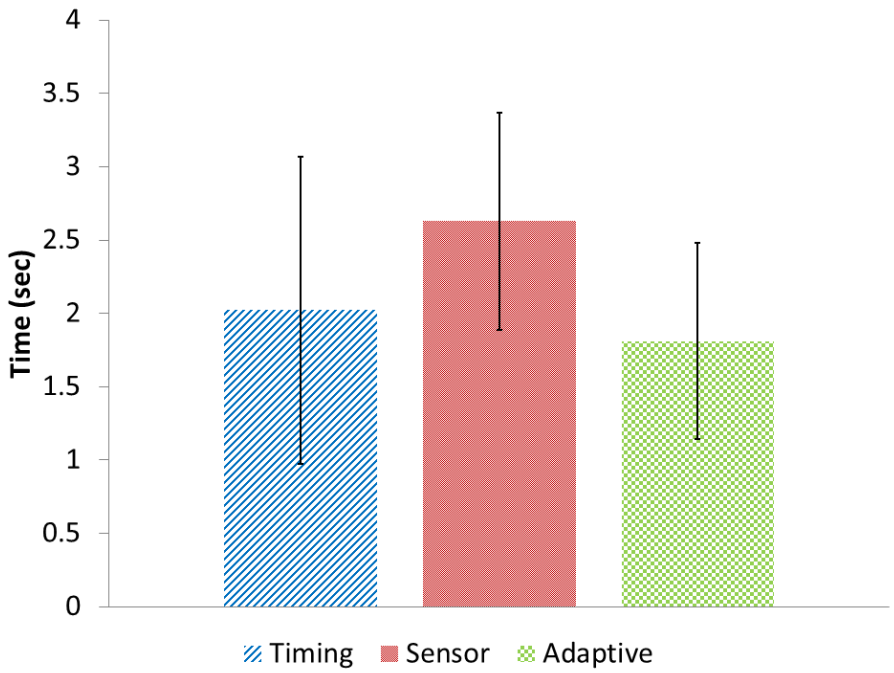



**Figure 7.9 The total idle time for timing, sensor and adaptive model respectively**

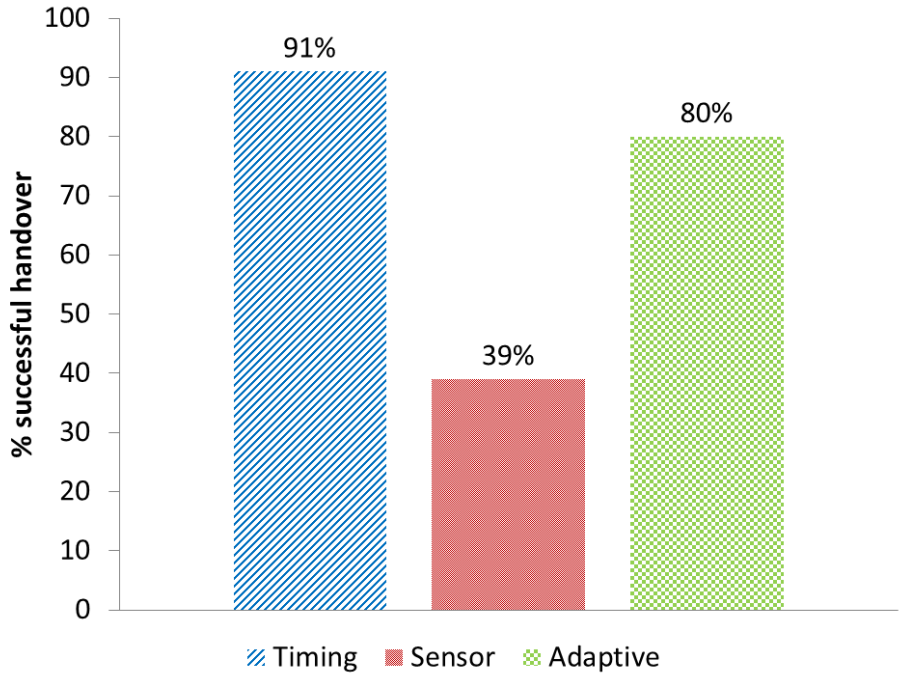
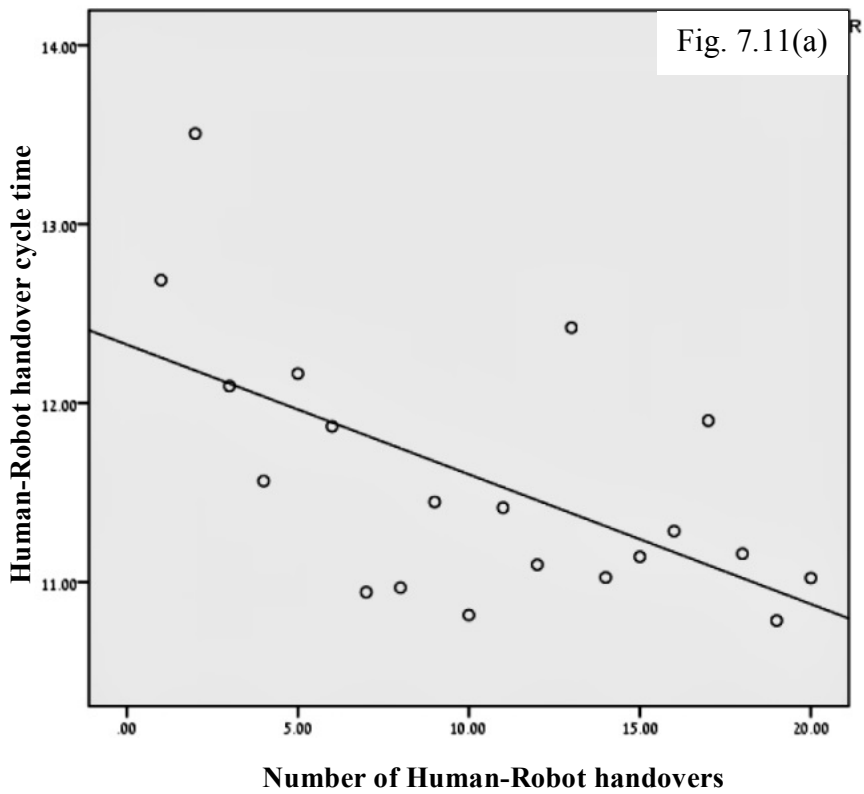
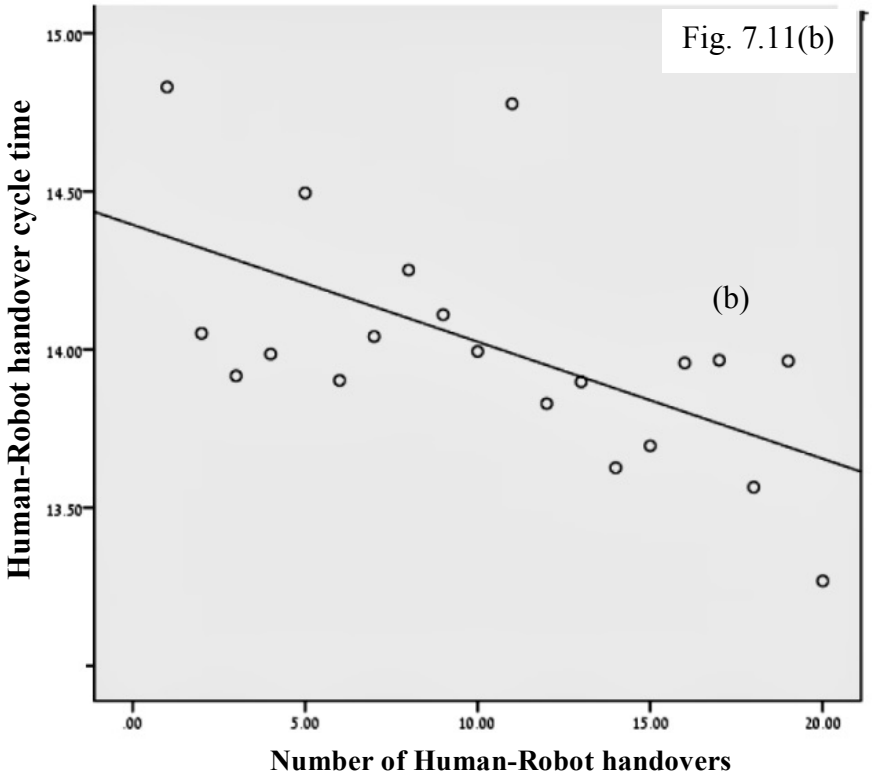
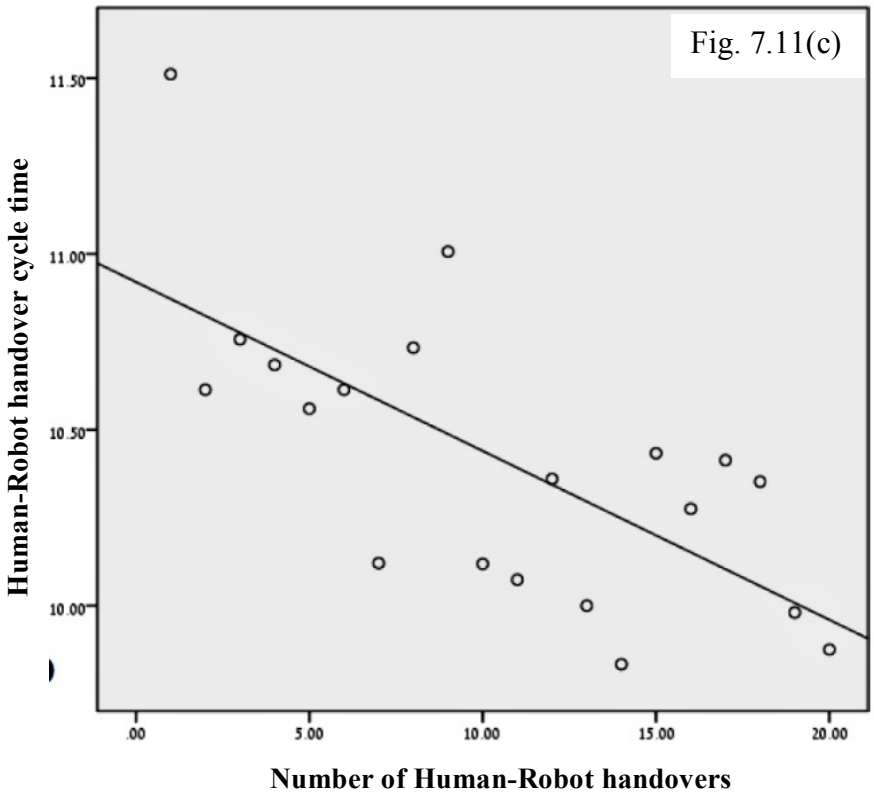



**Figure 7.10 Rate of successful handover in timing, sensor and adaptive model**






(c)

**Figure 7.11 Task learning curve for (a) timing (b) sensor and (c) adaptive model**

### 7.4.4. Discussion

Results indicate that there is a significant decrease in the total assembly time for the timing control model in comparison to the sensor control (30%) and adaptive models (10%). The adaptive model also fared substantially well against the sensor control model in decreasing the total assembly time by 20%. The performance of the timing and adaptive models are also significantly better than the sensor control model in decreasing the total idle time by 30% and 23% respectively. The timing control model also had the highest rate (91%) of successful handovers which implies that the robot functional delay is the least in this model.

Overall, it can be said that the timing control model is the best performing model followed by the adaptive model; the sensor control model is the worst performing model for short-cycle and simple tasks. This corresponds with the hypothesis that ***timing control model is best suited for short-cycle and simple tasks***.

## 7.5. Experiment III – Long and complex task

### 7.5.1. Experimental design

A long and complex task consisting of assembling four Lego characters – a dog, a tree, a doll and a toy car was chosen for this experiment. The robot workspace consists of a first-in-first-out stack of blocks representative of parts warehouse. The human workspace consists of the following items:

i. A blue box mounted with a proximity sensor.
ii. An instruction booklet – The task being complex, subjects were given a pictorial instruction booklet that illustrates the step-by-step process to build the respective structures.
iii. On the other side of the human workspace, 2 x 6 sets of glasses are provided and are representative of small parts and tools warehouse.

Six H-R handover cycles are needed to accomplish the given collaborative task. Two glasses are assigned for each H-R handover cycles (hence, 2 x 6 sets of glasses). These 12 glasses are numbered from 1 to 12 and filled with the necessary pieces for the assembly of the components assigned for the respective H-R handover cycle. The human is assigned with two sub-assembly tasks – I and II – to be done sequentially for each H-R handover cycle. Each glass is assigned for the respective sub-assembly (I or II) of the respective

handover cycle. When the human finishes executing the task for the sixth handover cycle, the collaborative task of assembling the four Lego characters is completed.

The twelve sub-assembly tasks are unique, have different levels of complexity and cognitive demand and require different amount of time to complete. Task complexity is analyzed on the basis of the human temporal variability in accomplishing the given task during the pilot experiment. The average execution times of each of the sub-assemblies are thus different. Subjects went through a practice session immediately before the main experiment due to the complexity of the task.

The following seven steps explain the given human-robot collaborative task:

a) The robot hands over a piece to the human. It consists of four Lego blocks plugged together as a cuboid.

b) The human dismantles this given piece into 4 parts.

c) The human then plugs any one of these four pieces into the Lego platform fixed within the blue box.

d) Only when the above step has been successfully done, the human can fetch the respective glass assigned for sub-assembly I of the respective handover cycle. The human assembles the given components following the instructions in the information booklet.

e) After sub-assembly I is over, the human plugs the second piece obtained from step 2 into the same blue box as in step 3.

f) The human can now proceed to fetch the respective glass assigned for sub-assembly II of the respective handover cycle. The human assembles the given components following the instructions in the information booklet.

g) After sub-assembly II is over, the human plugs the remaining third and fourth pieces obtained from step 2 into the same blue box as in step 3. And, this completes one H-R handover cycle.

A proximity sensor is mounted on the blue box which gets triggered every time the human works with it. During the course of the experiment, the human plugs the dismantled Lego blocks thrice into a Lego platform in the blue box thereby triggering a signal – at the beginning of sub-I, after the conclusion of sub-I and after the conclusion of sub-II.

Fig. 7.12a

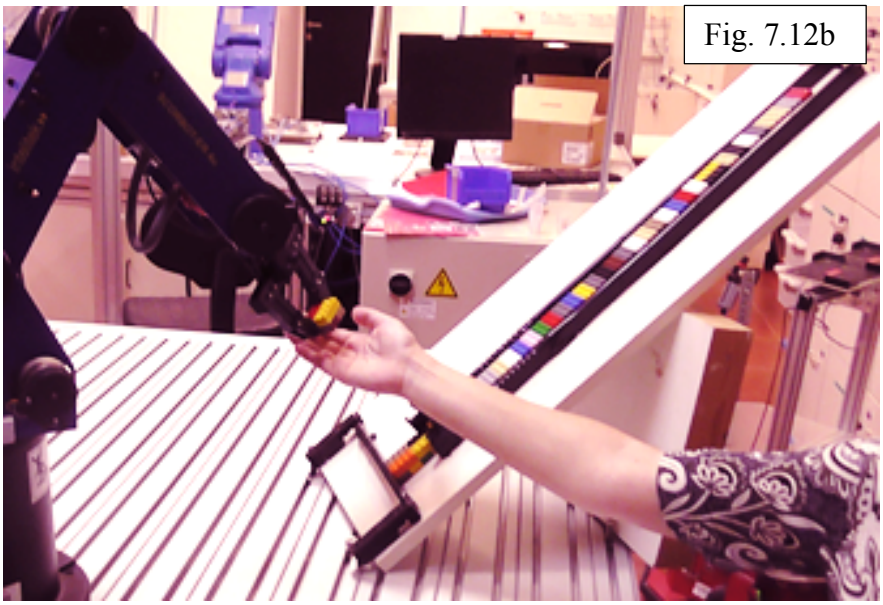


Fig. 7.12b

Fig. 7.12c

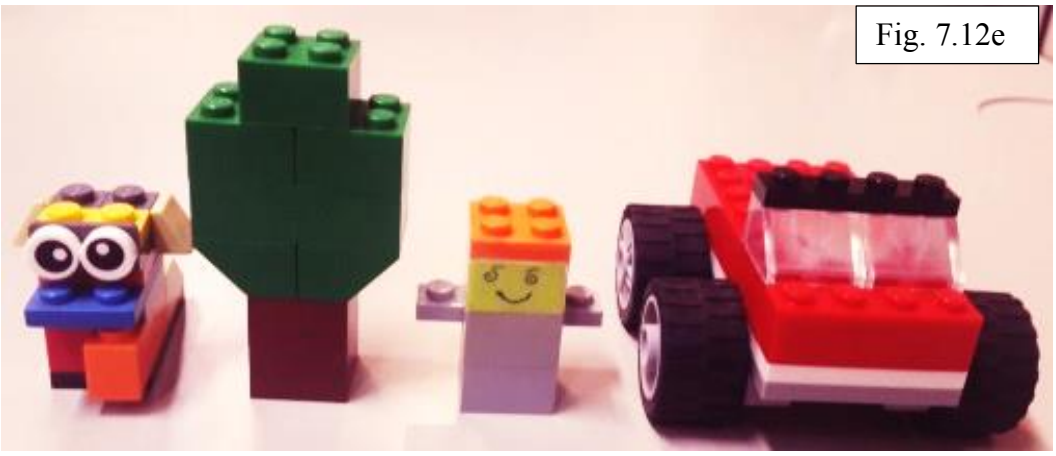



**Figure 7.12 The Human-Robot collaborative team-work in Experiment III (a) the robot picks up a Lego block from parts warehouse (b) the robot-human handover (c) the human fetches the respective glass assigned for sub-assembly (I and later II) (d) the human assembles the given components (e) the final output of the collaborative team-work**

### 7.5.2. Performance measures

Rate of successful handovers was recorded manually using a stop watch mobile app in an android smartphone. Robot idle time, human idle time, human assembly time and length of each H-R handover cycle were computed automatically using the sensors in the work cell.

### 7.5.3. Implementation

The three H-R collaboration models were implemented in the following way:

(i) **Timing control model**: The robot delivered the necessary pieces at fixed pre-defined time intervals. However, unlike the other two experiments, in this case, the pre-defined time between each handover cycle is different (it varies from 21 sec to 65 sec). It varies for the

six H-R handovers depending upon the length and complexity of each of the six cycles. This time interval is calculated by averaging the data collected during a pilot experiment.

(ii) **Sensor control model**: The sensors mounted on the robot gripper and in the human workspace helps the robot to keep track of the temporal state of the human action using three measures (i) time taken for sub-assembly I (ii) notification of the end of sub-assembly I (iii) time taken for sub-assembly II. The robot anticipates the time of the next H-R handover cycle in the following way:

a) It calculates the difference between the time taken for sub-assembly I by the current subject and the average time taken for sub-assembly I during the pilot experiment for that particular H-R handover cycle.
b) If the value is positive / negative, i.e., if the current subject has completed it slower / faster than the average, the robot anticipates the human to finish the sub-assembly II of that particular H-R handover cycle comparatively slower/faster than the average respectively. The robot calculates the tentative time-period of sub-assembly II using the formula below:

$$T = x \pm x\left\{1 - \frac{a}{b}\right\}$$

where,

T = time-period of sub-assembly II for the current subject

$x$ = avg. time-period of sub-assembly II (calculated from pilot experiment)

$a$ = time-period of sub-assembly I for the current subject

$b$ = avg. time-period of sub-assembly I (calculated from pilot experiment)

c) The robot prepares for the subsequent H-R handover cycle and arrives at the pre-determined point of handover after $T$ seconds (as calculated above) from the end of sub-assembly I.

(iii) **Adaptive model**: The robot continuously anticipates and temporally adapts to the working speed of the human in a collaborative task consisting of 6 H-R handover cycles of different lengths and complexity. The six sub-tasks of the six cycles are further classified into three groups – easier, medium and difficult – by determining its complexity level based on the human temporal variability of that sub-task during the pilot experiment. The algorithm predicts the time-period of the $n^{th}$ handover cycle based on –

a) Avg. time-period of the $n^{th}$ cycle for all the previous subjects

b) Profiling of the current subjects (fast / medium / slow) based on his/her relative performance in the previous handover cycles in comparison to the pilot population average. Highest weight is given to the subject's performance in the difficult cycles followed by medium and easier ones. For example, if the time taken by the current subject for a difficult sub-task is smaller than the average of the pilot population, then the robot profiles the subject as 'fast'.

The temporal predictive model determined the timing of the H-R handover. The prediction formula is given below:

$$F_i = a_i + \alpha * D_i + (1 - unpre)[\beta * C_i + \gamma * Q_i + \delta * FAST + \theta * SLOW + \varepsilon * MED]$$

where,

$F_i$ = the predicted $i^{th}$ cycle time (temporal prediction of the $i+1^{th}$ handover moment)

$D_i$ = pilot population avg. time-period of the Sub-assembly II of the $i^{th}$ cycle

$C_i$ = avg. of the time taken by the current subject for Sub-Assembly II of the $i^{th}$ cycle in the previous model

$Q_i$= performance comparison in Sub-Assembly I of the $i^{th}$ cycle in the previous model and the current model by the current subject.

$FAST,\ SLOW,\ MED$ = profiling (classification) of the current subject as fast, slow or medium based on the performance in the previous model. If this is the first model, no profiling is done and hence they are set to zero

*unpre* = when the subject's performance is not consistent and hence cannot be profiled into any of the categories, the unpredictable variable *unpre* is set to 1 and any prior profiling of the subject as fast, medium or slow is reset. As a result, the prediction will be done on the basis of the average of the population only. The value of *unpre* is set to zero otherwise.

$\alpha, \beta, \gamma, \delta, \theta, \varepsilon$ = constants (weights that were defined based on 10 pilots). The values of the weights $\alpha, \beta, \gamma, \delta, \theta, \varepsilon$ were calculated manually based on the pilot experiment data.

### 7.5.4. Results

(a) **Total assembly time**: Analysis of the data relating to the total assembly time indicated the following:

i. There are no significant differences (p=0.152) between the subjects ($H_0$ is not rejected in the one-way ANOVA with block.

ii. At least one of the models is significantly different (p=0.006) from the others (re-evaluation using the one-way ANOVA without block.

iii. There is a significant difference (p=0.002, p=0.04, respectively) between A & T and A & S (LSD test).

The total assembly time for the adaptive model is significantly lower (p=0.002, p=0.04) than the timing- and the sensor control model by 15% and 10% respectively (Fig. 7.13).

(b) **Total idle time**: Analysis of the data relating to the total idle time indicated the following:

i. There are no significant differences (p=0.447) between the subjects ($H_0$ is not rejected in the one-way ANOVA with block.

ii. At least one of the models is significantly different (p=0.001) from the others (re-evaluation using the one-way ANOVA without block.

iii. There is a significant difference (p=0.001, p=0.001, p=0.001, respectively) between each of the models, i.e., between T & S, A & T and A & S (LSD test).

The total idle time for the adaptive model is significantly lower (p=0.00, p=0.00) than the timing- and the sensor control model by 48% and 34% respectively (Fig. 7.14).

(c) **Rate of successful handovers**: Logistic regression results indicate that the timing and sensor control models are significantly different (p=0.0001, p=0.001 respectively) from the adaptive model. The highest number of successful handovers (34%) was obtained for the adaptive model followed by sensor control model with 19% success rate (Fig. 7.15).

(d) **Task learning curve**: Spearman's correlation coefficient was calculated for the data resulting $\rho_{Timing-Sensor} = 0.24$, $\rho_{Timing-Adaptive} = 0.95$, $\rho_{Sensor-Adaptive} = 0.068$, thereby indicating that the learning effect on the models is significantly negligible. Subjects went through a round of practice session immediately before the experiment to get

acquainted with the given complex task. It also probably helped in cancelling any possible learning effect.

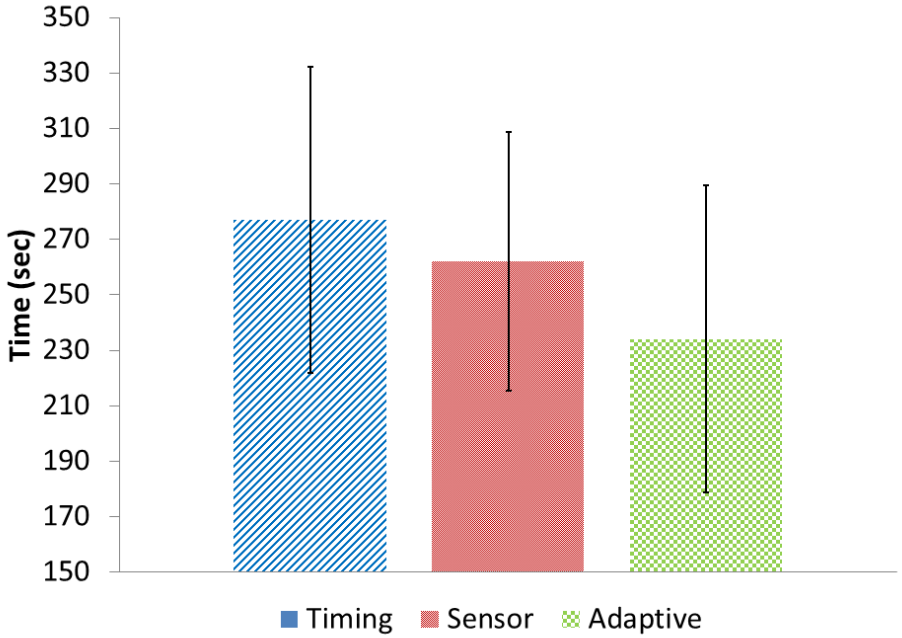



**Figure 7.13 The total assembly time for timing, sensor and adaptive model respectively**

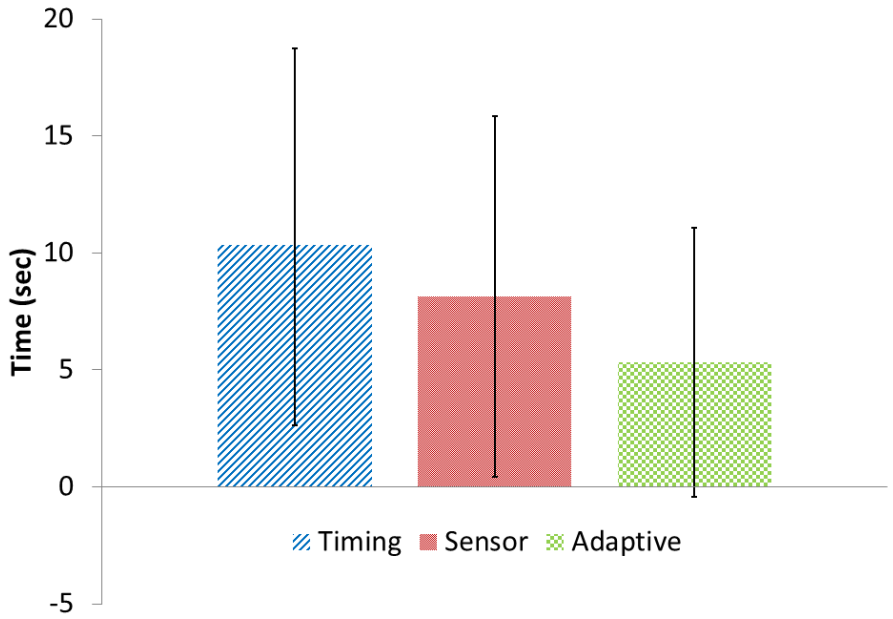



**Figure 7.14 The total idle time of the H-R system for timing, sensor and adaptive model respectively**

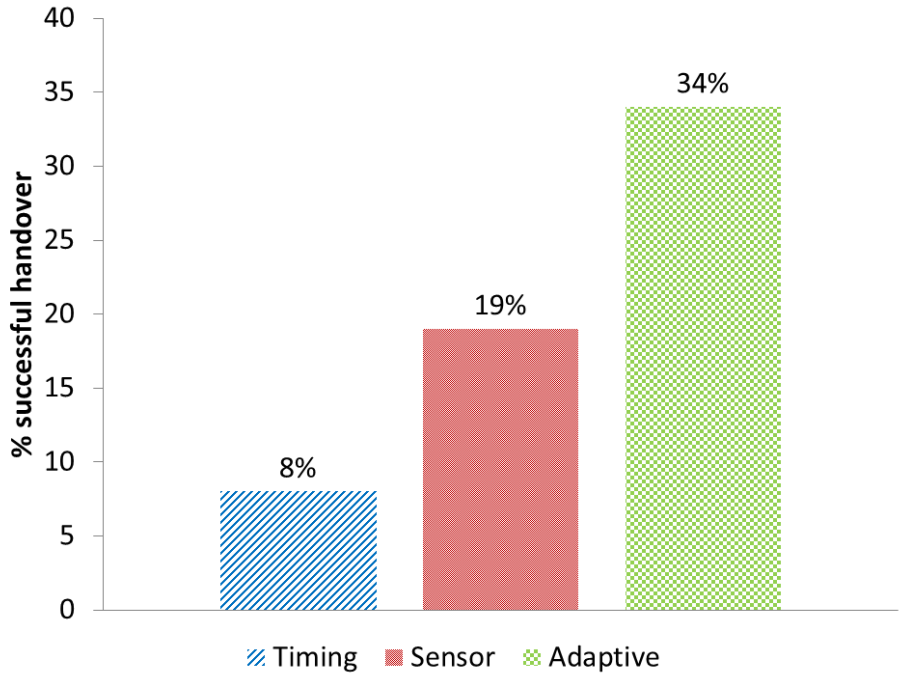



**Figure 7.15 Rate of successful handover**

### 7.5.5. Discussion

Results indicate that there is a substantial decrease in total idle time (48% and 34% respectively) and significant decrease (15% and 10% respectively) in total assembly time for adaptive model in comparison to timing- and sensor control model. The adaptive model also had the highest rate (34%) of successful handovers which implies that the robot functional delay is the least in this model. Overall, it can be said that adaptive model is the best performing model for the long and complex task. Therefore, our preliminary hypothesis that the adaptive model is best suited for this type of task holds true.

## 7.6. Conclusions

### 7.6.1. Adaptive model is best suited for long-cycle tasks (simple and complex):

The adaptive model achieves best performance measures for long cycle tasks (simple and complex). This is probably because, in a long-cycle task, human do not work in rhythm which in turn makes the fixed timing model less suitable. Since human variability in each cycle tends to be higher, a predictive and adaptive model best caters the needs of the user.

### 7.6.2. Timing control model is best suited for short-cycle and simple tasks

Short-cycle and simple tasks are generally rhythmic in nature. This makes the timing control model most suitable to build coordination between the human and the robot.

### 7.6.3. Sensor control model is least suited for short-cycle and simple task

A sensor control model leaves the robot with very little time (in a short-cycle task) at its disposal to sense, perceive and react after the triggering signal is received. This increases the robot functional delay, resulting in the human wait most of the times for the robot for the next H-R handover. This makes it the least preferred option in the case of short-cycle and simple tasks. The robot delay can be compensated to some extent by increasing the working speed of the robot. It may, however, make it unsafe for close proximity human-robot collaboration.

Furthermore, the sensors used in the three experimental studies are basic but highly reliable. As a result, real-time monitoring of the state of the human task could not be performed continuously. This limitation affected the overall performance of the sensor control model in all the experiments. Nevertheless, advanced sensor networks were not used because the end goal was to develop H-R collaboration models that can be readily implemented (i) in any industrial robots for collaborative manufacturing (ii) without requiring any design changes in factory floors (iii) with portability that is expected in a mobile manipulator (iv) with high sensor data reliability required in the extreme operating conditions in industries.

### 7.6.4. Well-coordinated Human-Robot teams have higher team productivity

The study of human-human joint-action revealed that "*the teams belonging to the category of 'best performers' in terms of productivity are, in fact, the most poorly coordinated teams*". When the speed of human-human joint-action increases, it also leads to higher variance in movements (poor coordination) following Fitts Law of speed-accuracy trade off. Higher variance, however, in this case is leading to higher productivity. This is because humans have advanced perception and cognitive skills, which allows the team-partners to adapt quickly in real-time to the constantly changing and unpredictable working speed of the other. As a result, the higher the speed of joint-action, the higher are the number of handovers irrespective of the lack of coordination and hence, the team productivity is higher.

This observation, however, is only valid to human-human joint-action and cannot be translated to Human-Robot team-work where robots have limited sensing and perception abilities. When the human task time has higher variance, it makes the handover unpredictable, and hence, difficult for the collaborating team-partner (the robot) to adapt accordingly in real-time. As a result, higher variance will result in poor-coordination and higher idle times in the case of H-R systems. Thus, the lower the human variance, the higher is the predictability of the human action and hence, higher is the team-coordination and productivity of the H-R team. The results of the three experiments indicate that the H-R collaboration models with the least total idle time and the highest number of successful handovers (implying better coordination) also has the least total assembly time (implying higher team productivity). Thus, it can be said that *well-coordinated Human-Robot teams have higher team productivity.*

# Chapter 8 | Conclusions and Future Work

***Chapter Overview***

The first part of this chapter deals with the limitations of the current study. This is followed by the general conclusions of this dissertation. It is further elaborated in the form of system design guidelines for H-R collaborative systems. The design guidelines are divided into four sections (from 8.3.1 to 8.3.4), corresponding to the studies of human-human joint action (chapter 4), analytical and simulation study of H-R collaborative system (chapter 6) and experimental study of H-R collaborative system (chapter 7). The chapter concludes with several recommendations for future work.

## 8.1. Limitations of the current work

### 8.1.1. Study of human-human joint action

The current work focuses on the subjective experience and psychological perspective of givers and receivers in short-cycle repetitive tasks. The objective measures presented are limited. As a result, the objective and the subjective measures could not be contrasted for bias or consistency.

Despite this, the work-methods field study has been instrumental in designing the set-up of the lab experiments and most importantly towards defining the experiments parameters and conditions. Similarly, the simulation study gave insights on the ergonomic aspects of givers and receivers which also influenced the design of the lab experiment (for example, it helped us decide that the alignment of giver (G), receiver (R) and the matrix of bottles (B) should be R-B-G and not R-G-B. That is, when the bottles are kept in between the giver and receiver, it is comparatively less tiring for the giver.

The simulation software used in this work did not offer the flexibility of modeling the actual movements recorded during the lab experiment. Using other software that offers such possibility may help to characterize the variability of energy according to different techniques/experience/body shapes etc.

### 8.1.2. Study of H-R collaborative system

1. The performance measures used in this research for temporal coordination in an H-R team is based on the previous work done in the area of H-R collaboration (Hoffman and

Breazeal 2007; Hoffman and Breazeal 2010; Shah 2011; Hoffman 2013; Lasota and Shah 2015). However, these measures are “ad-hoc” and “non-validated” (Hoffman and Breazeal 2007; Hoffman and Breazeal 2010; Hoffman 2013) to measure temporal coordination of H-R system.

2. The experimental study of the H-R collaborative system investigated in this dissertation included limited subjective metrics in only one of the three experiments.
3. Experimental analysis of short and complex tasks was not studied in this dissertation.
4. The adaptive model developed for the current study is basic and can be substantially improved.
5. The sensors used in this study are basic but highly reliable. As a result, real-time monitoring of the state of the human task could not be performed continuously. This limitation affected the performance of the sensor control model. Nevertheless, advanced sensor networks were not used because the end goal was to develop H-R collaboration models that can be readily implemented (i) in any industrial robots for collaborative manufacturing (ii) without requiring any design changes in factory floors (iii) with portability that is expected in a mobile manipulator (iv) with high sensor data reliability required in the extreme operating conditions in industries.
6. The analytical study done on H-R collaborative system is limited in scope since collaborative scenarios involving complex influencing parameters like user-proficiency and system reliability characteristics make the problem computationally intensive and complex.
7. The variability in human performance and robot action time were included in the simulation study using total cycle time standard deviations. Mathematical equations can be used in future research to represent the variability in human performance over prolonged time, like e.g., muscle fatigue and recovery model (Sadrfaridpour et al. 2014).
8. All the investigated influencing parameters were not studied using all the three methods – analytical, simulation and experimental. For example, the real effect of task length and complexity can be studied only by experimental studies on human subjects.
9. The speed of approach of the robot towards the point-of-handover was constant.

10. The human-robot handovers took place at the pre-defined point in space in every handover cycle. No spatial analysis or optimization was done. The robot also picked up the 'job' to be delivered to the human from pre-defined coordinates.

This summarizes the limitations of this dissertation. In the following section, general conclusions and the major findings of the overall study is presented.

## 8.2. General conclusions

This dissertation has dealt with the development and investigation of different aspects of temporal coordination among a collaborating human and a robot working in a team sharing work- and time-space for a collaborative handover task. The problem was approached by taking a bottom-up approach, combining behavioral research and quantitative models to determine the effective coordination strategy for human-robot collaboration with better team-coordination and improved system productivity.

The research included studies on human-human joint action based on which three Human-Robot collaboration models – *Timing, Sensor and Adaptive* – were developed for H-R team-work in a handover task. These models were evaluated using analytical, simulation and experimental studies.

The study on human-human joint-action revealed, among other things, the differences in the way individual team partners perceive a common joint-action depending upon their role (giver/receiver). Results also indicated the crucial role of temporal perception and prediction in the success of collaborative handover tasks. The three human-robot collaboration models were developed based on the basic principles of how humans perceive and process time,

The behavior of the H-R collaborative system in each of the three collaboration models was studied and compared using analytical, simulation and experimental studies for different influencing parameters. The case-studies show how the developed methodology can be used to study H-R collaborative systems and derive effective coordination strategies and system design guidelines presented in the next section of this chapter.

The collaboration models were further evaluated in real-world conditions by designing an integrated human-robot collaborative work-cell that facilitated close human-robot

interaction in a shared work-, time-space for time-critical tasks. Three experiments with 200 subjects in total were conducted to validate, evaluate and compare the models. The study helped to understand the strengths and limitations of each of the collaboration models and their specific suitability for different tasks type. Among others, results indicate that while the *Timing Control Model* is best suited for short and simple tasks, the *Adaptive Model* is best suited for long and simple, and long and complex tasks. The experiments also demonstrated the importance of time-perception in a human-robot collaborative system.

## 8.3. Human-Robot system design guidelines

The design guidelines below are based on the implications from the conclusions of the studies on (a) human-human joint-action, (b) analytical, (c) simulation, and (d) experimental study. Each of the recommended guidelines is related to the specific derived source in the relevant section and indicated if this is a direct or indirect implication.

### 8.3.1. Human-Human joint-action

1. In a repetitive H-R handover tasks involving considerable bending and lifting of goods (e.g., in supermarkets, warehouses), the robot should replace the job of a giver. (directly implied from 4.6.1).

2. Humans in general prefer to stick to their roles and habits (directly implied from 4.6.2.3 – *Habit Persistence in Decision Making*). Hence, we imply they would prefer to stick to their own convenient working pace. So, in general, the collaborative robot should be able to adapt and learn the preference of the user to offer more personalized service. An option to save the preferences and profile of each user in robot's database is thus recommended.

3. Any H-R system for collaborative tasks should be able to play both the role of a giver and a receiver to be able to work in any given role, depending upon the choice of the user (directly implied from 4.6.2.3). While a single arm robot with a mechanical double bottle holder may be able to accomplish the job of a giver, it will not be able to play the role of a dual-arm receiver, which also requires aligning the bottles on the shelf. Hence, a dual arm collaborative robot (like ABB Yumi and Baxter) is better suited to perform both of these roles in equal capacity (directly implied from 4.6.2.7 – *Preference towards* the *use of two hands*).

4. Humans prefer to work in normal mode in comparison to competitive mode (directly implied from 4.6.2.6 – *Does most comfortable/ergonomic work method when speeded up apparently gives a perception of most well-coordinated joint-action?*). So the default speed setting of the collaborative robot should be the average working speed of human, which is around 5 bottles per 10 seconds, as reported in Section 6.1. This will also provide less fatigue and stress.

5. Humans tend to be well-coordinated when they are in competitive mode of the most comfortable posture/work method. The vice-versa is also true (directly implied from 4.6.2.6). The minimum and maximum speed of each handover cycle can be set for the collaborative robot using this principle. This means, when a robot is working together with a receiver in the lower shelf-competitive mode, it should not exceed beyond 7 or 8 bottles/10 sec (5 bottles/10 sec, being average for normal mode) to avoid early fatigue of workers. The handover cycle frequency may go upto 9 bottles/10 sec during a higher shelf-competitive mode because the receiver finds it to be the most comfortable work-posture to collaborate.

6. A robot with a fixed periodic motion and a fixed p-o-h pre-set by the respective user is better suited than highly accurate systems with non-rhythmic or reactive motions for short-cycle repetitive handover task (implied from Section 4.6).

### 8.3.2. Analytical study of Human-Robot collaborative system

1. The robot cycle time should not change in every H-R handover in repetitive tasks to improve the fluency of H-R coordination (implied from case-study I, Section 6.2.4).

2. In repetitive tasks, the H-R control system design should be a fusion of Timing and Sensor based control (implied from case-study II, Section 6.2.4 and 6.10.3).

### 8.3.3. Simulation study of Human-Robot collaborative system

1. It is always better for a novice user to work slowly with the robot for comparatively better H-R coordination (implied from case-study III, Section 6.7).

2. The fluency of H-R coordination depends on the given scenario and the given set of conditions (implied from case-study III, IV, V, VI, Section 6.7 and 6.8).

3. If a system does not have the ability to recalibrate itself, it is always better to maintain a tendency to arrive faster and before the robot (implied from case-study IV, Section 6.7).

4. If the functionality of *recalibration* (under certain threshold) is added to the H-R system, the fluency of H-R coordination can be improved (implied from case-study IV, Section 6.7).
5. A novice user can maintain a higher fluency of H-R coordination with the robot if the system has the ability to recalibrate itself (implied from case-study IV, Section 6.7).
6. When the robot has an unpredictable speed in its sequence of action, it is always better to collaborate as slow as possible to improve the fluency of H-R coordination (implied from case-study V, Section 6.8).
7. Timing based control model could be a better option than sensor- based control for a system with unreliable or inferior quality sensors (implied from case-study III and V, Section 6.7 and 6.8, respectively).

### 8.3.4. Experimental study of Human-Robot collaborative system

The following guidelines are based on the experimental study of H-R collaboration models as discussed in Chapter 7:

1. Adaptive model is best suited for long-cycle tasks (simple and complex) (implied from the conclusions of experiment 1 and 3, Section 7.6.1).
2. Timing control model is best suited for short-cycle and simple tasks (implied from the conclusions of experiment 2, Section 7.6.2).
3. Sensor control model is least suited for short-cycle and simple task (implied from the conclusions of experiment 2, Section 7.6.3).
4. The study of human-human joint-action revealed that "*the teams belonging to the category of 'best performers' in terms of productivity are, in fact, the most poorly coordinated teams*". This is only valid for human-human joint-actions and cannot be translated to human-robot systems. The results of all the three experiments showed that the H-R collaboration model with the least total idle time and the highest number of successful handovers (implying better coordination) also had the least total assembly time (implying higher team productivity). *So, well-coordinated Human-Robot teams have higher team productivity.*

## 8.4. Recommendations for future work

Future work recommendations include:

1. The development of a hybrid control system with the ability to switch dynamically between the three H-R collaboration models (timing / sensor / adaptive) depending upon the needs of the task and of the user. Research should focus on the timing and frequency of switching and on the level of automation in switching.
2. Development of a methodical approach to define and validate temporal coordination metrics of H-R system.
3. Subjective measures must be included in all the experiments on H-R collaborative team-work so as to link the objective and subjective measures and scientifically validate the metrics for measuring temporal coordination in H-R system.
4. Experimental analysis of short and complex tasks should be performed to assess the suitability of the developed H-R collaboration models for these task types.
5. Development of advanced adaptive model for H-R collaboration.
6. Human-human joint-action future research should include a more detailed investigation of the actual movements from video analysis or by motion tracking with passive markers or wearable sensors which can then be contrasted with the subjective measures of this experiment to get a broader understanding of human-human joint-action in the areas investigated in this research.
7. Experiments on H-R collaborative team-work should extend over several hours to measure the real life effect of the investigated influencing parameters (user-proficiency, learning/fatigue, task length and complexity, etc.) on temporal coordination in human-robot collaboration.

# References


Agnetis A (2000) Scheduling no-wait robotic cells with two and three machines. Eur J Oper Res 123:303–314. doi: 10.1016/S0377-2217(99)00258-1

Akturk MS, Gultekin H, Karasan OE (2005) Robotic cell scheduling with operational flexibility. Discret Appl Math 145:334–348. doi: 10.1016/j.dam.2004.02.012

Al-Hinai N, Elmekkawy TY (2011) An efficient hybridized genetic algorithm architecture for the flexible job shop scheduling problem. Flex Serv Manuf J 23:64–85. doi: 10.1007/s10696-010-9067-y

Arviv K, Stern H, Edan Y (2015) Collaborative reinforcement learning for a two-robot job transfer flow-shop scheduling problem. International Journal of Production Research 7543:1–14. doi: 10.1080/00207543.2015.1057297

Basili P, Huber M, Brandt T, et al (2009) Investigating Human-Human Approach and Hand-Over. Hum Centered Robot Syst 6:151–160. doi: 10.1007/978-3-642-10403-9

Bausenhart KM, Rolke B, Seibold VC, Ulrich R (2010) Temporal preparation influences the dynamics of information processing: evidence for early onset of information accumulation. Vision Res 50:1025–34. doi: 10.1016/j.visres.2010.03.011

Bechar A, Edan Y (2003) Human-robot collaboration for improved target recognition of agricultural robots. Ind Robot An Int J 30:432–436. doi: 10.1108/01439910310492194

Bechar A, Meyer J, Edan Y (2009) An Objective Function to Evaluate Performance of Human–Robot Collaboration in Target Recognition Tasks. IEEE Trans Syst Man Cybern Part C Appl Rev 39:611–620. doi: 10.1109/TSMCC.2009.2020174

Ben-Gal I, Bukchin J (2002) The ergonomic design of workstations using virtual manufacturing and response surface methodology. IIE Trans 34:375–391. doi: 10.1080/07408170208928877

Bernardin HJ, Cooke DK, Villanova P (2000) Conscientiousness and agreeableness as predictors of rating leniency. J Appl Psychol 85:232–236. doi: 10.1037/0021-9010.85.2.232

Bischoff R, Kurth J, Schreiber G, et al (2010) The KUKA-DLR Lightweight Robot arm – a new reference platform for robotics research and manufacturing. Jt 41th Int Symp Robot 6th Ger Conf Robot 741–748.

Bosch T, Mathiassen SE, Hallman D, et al (2012) Temporal strategy and performance during a fatiguing short-cycle repetitive task. Ergonomics 55:863–873.

Boucher JD, Pattacini U, Lelong A, et al (2012) I reach faster when i see you look: Gaze effects in human-human and human-robot face-to-face cooperation. Front Neurorobot. doi: 10.3389/fnbot.2012.00003

Bratman M (1992) Shared cooperative activity. Philos Rev 101:327–341. doi: 10.2307/2185537

Byström K, Järvelin K (1995) Task Complexity Affects Information. Inf Process Manag 31:191–213. doi: 10.1016/0306-4573(95)80035-R

Cakmak M, Srinivasa SS, Lee MK, et al (2011) Using spatial and temporal contrast for fluent robot-human hand-overs. In: Proceedings of the 6th international conference on Human-robot interaction. ACM, pp 489–496

Casper J, Murphy RR (2003) Human – Robot Interactions During the Robot-Assisted Urban Search and Rescue Response at the World Trade Center. IEEE Trans Syst Man Cybern 33:367–385.

Chaffin DB, Page GB (1994) Postural effects on biomechanical and psychophysical weight-lifting limits. Ergonomics 37:663–676. doi: 10.1080/00140139408963681

Cherubini A, Passama R, Crosnier A, et al (2016) Collaborative manufacturing with physical human–robot interaction. Robot Comput Integr Manuf 40:1–13. doi: 10.1016/j.rcim.2015.12.007

Clodic A, Alami R, Chatila R (2014) Key Elements for Joint Human-Robot Action. Sociable Robot

Futur Soc Relations Proc Robo-Philosophy 23–33. doi: 10.3233/978-1-61499-480-0-23

Cohen R, Rosenbaum D (2004) Where grasps are made reveals how grasps are planned: generation and recall of motor plans. Exp Brain Res 157:486–495. doi: 10.1007/s00221-004-1862-9

del Rio Vilas D, Longo F, Rego-Monteil N (2012) A general framework for the manufacturing workstation design optimization: a combined ergonomic and operational approach. Simul Trans Soc Model Simul Int 89:306–329. doi: 10.1177/0037549712462862

Dempsey PG, Mathiassen SE, Jackson JA, O'Brien N V (2010) Influence of three principles of pacing on the temporal organisation of work during cyclic assembly and disassembly tasks. Ergonomics 53:1347–1358. doi: 10.1080/00140139.2010.520745

Ding H, Schipper M, Matthias B (2014) Optimized task distribution for industrial assembly in mixed human-robot environments - Case study on IO module assembly. 2014 IEEE Int Conf Autom Sci Eng 19–24. doi: 10.1109/CoASE.2014.6899298

Ding H, Schipper M, Matthias B (2013) Collaborative behavior design of industrial robots for multiple human-robot collaboration. 2013 44th Int Symp Robot ISR 2013. doi: 10.1109/ISR.2013.6695707

Duan F, Tan J (2011) A new human-robot collaboration assembly system for cellular manufacturing. Control Conf (CCC), 2011 5468–5473.

Duan F, Tan J, Tong J, Kato R (2012) Application of the Assembly Skill Transfer System in an Actual Cellular Manufacturing System. Autom Sci 9:31–41.

Dynan KE (2000) Habit formation in consumer preferences: Evidence from panel data. Am Econ Rev 90:391–406. doi: 10.1257/aer.90.3.391

Eccles DW, Tenenbaum G (2004) Why an Expert Team is More Than a Team of Experts: A Social-Cognitive Conceptualization of Team Coordination and Communication in Sport. J Sport Exerc Psychol 26:542–560.

Eilon S (1964) On a mechanistic approach to fatigue and rest periods. Int J Prod Res 3:327–332. doi: 10.1080/00207546408943065

Fitzgerald C (2013) Developing Baxter. In: IEEE Conference on Technologies for Practical Robot Applications, TePRA. pp 1–6

Fraenkel P (1994) Time and rhythm in couples. Fam Process 33:37–51.

Galati A, Avraamides MN (2013) Flexible spatial perspective-taking: conversational partners weigh multiple cues in collaborative tasks. Front Hum Neurosci 7:618. doi: 10.3389/fnhum.2013.00618

Garg A, Hegmann K, Kapellusch J (2006) Short-cycle overhead work and shoulder girdle muscle fatigue. Int J Ind Ergon 36:581–597. doi: 10.1016/j.ergon.2006.02.002

Gentzler GL, Khalil TM, Sivazlian BD (1977) Quantitative models for optimal rest period scheduling. Omega 5:215–220. doi: http://dx.doi.org/10.1016/0305-0483(77)90104-9

Gharbi M, Paubel PV, Clodic A, et al (2015) Toward a better understanding of the communication cues involved in a human-robot object transfer. Proc - IEEE Int Work Robot Hum Interact Commun 319–324. doi: 10.1109/ROMAN.2015.7333626

Glasauer S, Huber M, Basili P (2010) Interacting in time and space: Investigating human-human and human-robot joint action. RO-MAN, 2010 252–257.

Gombolay M, Wilcox R, Shah J (2013a) Fast Scheduling of Multi-Robot Teams with Temporospatial Constraints. In: Robotics: Science and Systems. pp 1–8

Gombolay MC (2013) Fast Methods for Scheduling with Applications to Real-Time Systems and Large-Scale , Robotic Manufacturing of Aerospace Structures by.

Gombolay MC, Wilcox RJ, Diaz A, et al (2013b) Towards Successful Coordination of Human and Robotic Work using Automated Scheduling Tools: An Initial Pilot Study. In: Robotics: Science and Systems, Human-Robot Collaboration Workshop.

Grand C, Mostafaoui G, Hasnain SK, Gaussier P (2014) Synchrony Detection as a Reinforcement Signal for Learning: Application to Human Robot Interaction. Procedia - Soc Behav Sci 126:82–91. doi: 10.1016/j.sbspro.2014.02.322

Guo S, Takahashi K, Morikawa K (2011) PCB assembly scheduling with alternative nozzle types for one component type. Flex Serv Manuf J 23:316–345. doi: 10.1007/s10696-011-9081-8

Haaijer R, Wedel M (2001) Habit Persistence in Time Series Models of Discrete Choice. Mark Lett 12:25–35. doi: 10.1023/A:1008163801995

Haddadin S, Suppa M, Fuchs S, et al (2011) Towards the robotic co-worker. In: Pradalier C, Siegwart R, Hirzinger G (eds) Robotics Research. Springer Berlin Heidelberg, Berlin, Heidelberg, pp 261–282

Harari Y, Bechar A, Riemer R (2017) Automated simulation – based workplace design that considers ergonomics and productivity. Int J Simul Model 16:In Press.

Herbort O, Koning A, van Uem J, G.J. Meulenbroek R (2012) The end-state comfort effect facilitates joint action. Acta Psychol (Amst) 139:404–416. doi: 10.1016/j.actpsy.2012.01.001

Hoffman G (2013) Evaluating Fluency in Human-Robot Collaboration. In: Robotics Science and Systems (RSS), Workshop on Human Robot Collaboration.

Hoffman G, Breazeal C (2007) Cost-Based Anticipatory Action Selection for Human–Robot Fluency. IEEE Trans Robot 23:952–961. doi: 10.1109/TRO.2007.907483

Hoffman G, Breazeal C (2010) Effects of anticipatory perceptual simulation on practiced human-robot tasks. Auton Robots 28:403–423. doi: 10.1007/s10514-009-9166-3

Howard A (2007) A Systematic Approach to Predict Performance of Human–Automation Systems. IEEE Trans Syst Man, Cybern Part C 37:594–601.

Howard A (2005) A Methodology to Assess Performance of Human-Robotic Systems in Achievement of Collective Tasks. In: International Conference on Intelligent Robots and Systems. pp 90–95

Huang C, Cakmak M, Mutlu B (2015) Adaptive Coordination Strategies for Human-Robot Handovers. In: Proceedings of the 11th Robotics: Science and Systems (RSS).

Huber M, Kupferberg A, Lenz C, et al (2013) Spatiotemporal Movement Planning and Rapid Adaptation for Manual Interaction. PLoS One. doi: 10.1371/journal.pone.0064982

Huber M, Lenz C, Rickert M, et al (2008) Human preferences in industrial human-robot interactions.

Iqbal T, Gonzales M, Riek L (2014) A Model for Time-Synchronized Sensing and Motion to Support Human-Robot Fluency.

Kamali J, Moodie C, Salvendy G (1982) A framework for integrated assembly systems: humans, automation and robots. Int. J. Prod. Res. 20:431–448.

Keller PE (2008) Joint Action in Music Performance. In: Enacting Intersubjectivity: A Cognitive and Social Perspective on the Study of Interactions. pp 205–221

Keller PE, Koch I (2008) Action planning in sequential skills: relations to music performance. Q J Exp Psychol (Hove) 61:275–291. doi: 10.1080/17470210601160864

Keller PE, Novembre G, Hove MJ (2014) Rhythm in joint action: Psychological and neurophysiological mechanisms for real-time interpersonal coordination. Philos Trans R Soc Lond B Biol Sci. doi: 10.1098/rstb.2013.0394

Keyfitz N, McNeill WH (1996) Keeping Together in Time: Dance and Drill in Human History. Contemp. Sociol. 25:408.

Khalid O, Caliskan D, Ore F, Hanson L (2015) Simulation and evaluation of industrial applications of Human- Industrial Robot Collaboration cases. In: 47th Annual Conference of Nordic Ergonomics and Human Factors Society.

Knoblich G, Butterfill S, Sebanz N (2011) Psychological Research on Joint Action: Theory and

Data. Psychol Learn Motiv Adv Res Theory, Vol 54 54:59–101. doi: Doi 10.1016/B978-0-12-385527-5.00003-6

Kozak M, Zeev N (2015) Work methods for repetitive tasks in collaborative work. In: Final Project Report. Ben-Gurion University of the Negev.

Kozima H, Michalowski MP, Nakagawa C (2008) Keepon. Int J Soc Robot 1:3–18. doi: 10.1007/s12369-008-0009-8

Krüger J, Lien TK, Verl A (2009) Cooperation of human and machines in assembly lines. CIRP Ann - Manuf Technol 58:628–646. doi: 10.1016/j.cirp.2009.09.009

Krüger J, Surdilovic D (2008) Robust control of force-coupled human-robot-interaction in assembly processes. CIRP Ann - Manuf Technol 57:41–44. doi: 10.1016/j.cirp.2008.03.005

Kuwabara K, Ishida T, Osato N (1995) AgenTalk: describing multiagent coordination protocols with inheritance. Proc 7th IEEE Int Conf Tools with Artif Intell 465:460–465. doi: 10.1109/TAI.1995.479841

Laderman J, Littauer SB, Weiss L (1953) The Inventory Problem. J Am Stat Assoc 48:717–732. doi: 10.1080/01621459.1953.10501195

Lasota PA, Shah JA (2015) Analyzing the Effects of Human-Aware Motion Planning on Close-Proximity Human-Robot Collaboration. Hum Factors 57:21–33. doi: 10.1177/0018720814565188

Levner E, Kats V, Levit VE (1997) An improved algorithm for cyclic flowshop scheduling in a robotic cell. Eur J Oper Res 97:500–508. doi: 10.1016/S0377-2217(96)00272-X

Lorenz T, Mortl A, Vlaskamp B, et al (2011) Synchronization in a goal-directed task: Human movement coordination with each other and robotic partners. In: Proceedings - IEEE International Workshop on Robot and Human Interactive Communication. pp 198–203

Lorenz T, Weiss A, Hirche S (2015) Synchrony and Reciprocity: Key Mechanisms for Social Companion Robots in Therapy and Care. Int J Soc Robot 8:125–143. doi: 10.1007/s12369-015-0325-8

Madison G, Merker BH (2005) Timing of action during and after synchronization with linearly changing intervals. Music Percept An Interdiscip J 22:441–459. doi: 10.1525/mp.2005.22.3.441

Maniadakis M, Trahanias P (2014) Time in Symbiotic Human Robot Interaction. In: Workshop on Timing in Human-Robot Interaction at the 9th ACM/IEEE International Conference on Human-Robot Interaction (HRI 2014).

Maniadakis M, Trahanias P (2011) Temporal cognition: A key ingredient of intelligent systems. Front Neurorobot 5:1–6. doi: 10.3389/fnbot.2011.00002

Matsas E, Batras D, Vosniakos G (2016) Modelling Simple Human-Robot Collaborative Manufacturing Tasks in Interactive Virtual Environments. 18th Virtual Real Int Conf (VRIC ’16) 4.

Merker BH, Madison GS, Eckerdal P (2009) On the role and origin of isochrony in human rhythmic entrainment. Cortex 45:4–17. doi: 10.1016/j.cortex.2008.06.011

Meyer M, Van Der Wel RPRD, Hunnius S (2013) Higher-order action planning for individual and joint object manipulations. Exp Brain Res 225:579–588. doi: 10.1007/s00221-012-3398-8

Michalos G, Makris S, Tsarouchi P, et al (2015) Design Considerations for Safe Human-robot Collaborative Workplaces. Procedia CIRP 37:248–253. doi: 10.1016/j.procir.2015.08.014

Michalowski MP, Sabanovic S (2007) A Dancing Robot for Rhythmic Social Interaction Hideki Kozima. 89–96.

Moon Aj, Troniak DM, Gleeson B, et al (2014) Meet me where i’m gazing: how shared attention gaze affects human-robot handover timing. Human-Robot Interact 334–341. doi: 10.1145/2559636.2559656

Moore A, Wells R (2005) Effect of cycle time and duty cycle on psychophysically determined acceptable levels in a highly repetitive task. Ergonomics 48:859–873. doi: 10.1080/00140130512331332909

Mörtl A, Lorenz T, Hirche S (2014) Rhythm patterns interaction - Synchronization behavior for human-robot joint action. PLoS One. doi: 10.1371/journal.pone.0095195

Mörtl A, Lorenz T, Vlaskamp BNS, et al (2012) Modeling inter-human movement coordination: Synchronization governs joint task dynamics. Biol Cybern 106:241–259. doi: 10.1007/s00422-012-0492-8

Moyal R, Goldshtein S (2015) An examination of Human-Robot cooperation models for different types of tasks. In: Final Project Report. Ben-Gurion University of the Negev.

Mutlu B, Terrell A, Huang C (2013) Coordination Mechanisms in Human-Robot Collaboration. In: International Conference on Human-Robot Interaction - Workshop on Collaborative Manipulation. pp 1–6

Namera K, Takasugi S, Takano KK, et al (2008) Timing control of utterance and body motion in human-robot interaction. In: Proceedings of the 17th IEEE International Symposium on Robot and Human Interactive Communication, RO-MAN. pp 119–123

Neuman GA, Wright J (1999) Team effectiveness: beyond skills and cognitive ability. J Appl Psychol 84:376–389. doi: 10.1037/0021-9010.84.3.376

Nikolaidis S, Kuznetsov A, Hsu D, Srinivasa S (2016) Formalizing Human-Robot Mutual Adaptation : A Bounded Memory Model. In: International Conference on Human-Robot Interaction. pp 75–82

Nikolaidis S, Lasota P, Ramakrishnan R, Shah J (2015) Improved human-robot team performance through cross-training, an approach inspired by human team training practices. Int J Rob Res 34:1711–1730. doi: 10.1177/0278364915609673

Nikolaidis S, Lasota P, Rossano G, et al (2013) Human-robot collaboration in manufacturing: Quantitative evaluation of predictable, convergent joint action. In: 44th International Symposium on Robotics (ISR).

Ore F, Hanson L, Delfs N, Wiktorsson M (2013) Virtual evaluation of industrial human-robot cooperation : An automotive case study. In: 3rd International Digital Human Modeling Symposium. pp 1–8

Oren Y, Bechar A, Edan Y (2012) Performance analysis of a human-Robot collaborative target recognition system. Robotica 30:813–826. doi: 10.1017/S0263574711001020

Parasuraman R, Sheridan TB, Wickens CD (2000) A model for types and levels of human interaction with automation. IEEE Trans Syst man, Cybern Part A Syst humans 30:286–97.

Repp BH, Keller PE (2004) Adaptation to tempo changes in sensorimotor synchronization: effects of intention, attention, and awareness. Q J Exp Psychol A 57:499–521. doi: 10.1080/02724980343000369

Richardson MJ, Marsh KL, Isenhower RW, et al (2007) Rocking together: Dynamics of intentional and unintentional interpersonal coordination. Hum Mov Sci 26:867–891. doi: 10.1016/j.humov.2007.07.002

Richardson MJ, Marsh KL, Schmidt RC (2005) Effects of visual and verbal interaction on unintentional interpersonal coordination. J Exp Psychol Hum Percept Perform 31:62–79. doi: 10.1037/0096-1523.31.1.62

Riemer R, Bechar A (2016) Investigation of productivity enhancement and biomechanical risks in greenhouse crops. Biosyst Eng 147:39–50. doi: 10.1016/j.biosystemseng.2016.03.009

Rosenbaum DA, Marchak F, Barnes HJ, et al (1990) Constraints for action selection: overhand versus underhand grips. Atten Perform XIII 321–342.

Rosenbaum DA, Van Heugten CM, Caldwell GE (1996) From cognition to biomechanics and back:

The end-state comfort effect and the middle-is-faster effect. Acta Psychol (Amst) 94:59–85. doi: 10.1016/0001-6918(95)00062-3

Sadrfaridpour B, Saeidi H, Wang Y, Burke J (2014) Modeling and Control of Trust in Human and Robot Collaborative Manufacturing. In: AAAI Spring Symposium Series: The Intersection of Robust Intelligence and Trust in Autonomous Systems. pp 64–70

Sanabria D, Capizzi M, Correa A (2011) Rhythms that speed you up. J Exp Psychol Hum Percept Perform 37:236–44. doi: 10.1037/a0019956

Sarkar N (2002) Psychophysiological control architecture for human-robot coordination-concepts and initial experiments. IEEE Int Conf Robot Autom 4:3719–3724. doi: 10.1109/ROBOT.2002.1014287

Sayfeld L, Peretz Y (2014) Evaluation of human-robot collaboration models for fluent operations in industrial tasks. In: Final Project Report. Ben-Gurion University of the Negev.

Sebanz N, Bekkering H, Knoblich G (2006) Joint action: Bodies and minds moving together. Trends Cogn. Sci. 10:70–76.

Sebanz N, Knoblich G (2009) Prediction in Joint Action: What, When, and Where. Top Cogn Sci 1:353–367. doi: 10.1111/j.1756-8765.2009.01024.x

Seifried T, Ulrich R, Bausenhart KM, et al (2010) Temporal preparation decreases perceptual latency: evidence from a clock paradigm. Q J Exp Psychol 63:2432–51. doi: 10.1080/17470218.2010.485354

Serfaty D, Entin EE, Johnston JH (1998) Team coordination training. In: Making decisions under stress: Implications for individual and team training. pp 221–245

Shah JA (2011) Fluid Coordination of Human-Robot Teams. In: Doctoral dissertation, Massachusetts Institute of Technology.

Shah JA, Conrad PR, Williams BC (2009) Fast distributed multi-agent plan execution with dynamic task assignment and scheduling. In: 19th International Conference on Automated Planning and Scheduling (ICAPS). pp 289–296

Siemens PLM (2015) Jack and Process Simulate Human.

Someshwar R, Kerner Y (2013) Optimization of waiting time in H-R coordination. IEEE Int Conf Syst Man, Cybern 1918–1923. doi: 10.1109/SMC.2013.330

Someshwar R, Meyer J, Edan Y (2012a) Models and Methods for HR Synchronization. 14th IFAC Symp Inf Control Probl Manuf 14:829–834.

Someshwar R, Meyer J, Edan Y (2012b) A Timing Control Model for HR Synchronization. 10th IFAC Symp Robot Control 10:698–703.

Stanescu AM, Nita A, Moisescu M a., Sacala IS (2008) From industrial robotics towards intelligent robotic systems. In: 4th International IEEE Conference on Intelligent Systems, IS'08. IEEE, pp 6–73

Strabala K, Lee MK, Dragan A, et al (2013) Toward Seamless Human – Robot Handovers. J Hum Robot Interact 2:112–132. doi: 10.5898/JHRI.2.1.Strabala

Sun Y, Sundar SS (2016) Psychological Importance of Human Agency. In: International Conference on Human-Robot Interaction. pp 189–196

Suri RE, Schultz W (2001) Temporal Difference Model Reproduces Anticipatory Neural Activity. Neural Comput 13:841–862. doi: 10.1162/089976601300014376

Tan JTC, Duan F, Zhang Y, et al (2009) Human-robot collaboration in cellular manufacturing: Design and development. In: IEEE/RSJ International Conference on Intelligent Robots and Systems. pp 29–34

Thunholm P (2004) Decision-making style: Habit, style or both? Pers Individ Dif 36:931–944. doi: 10.1016/S0191-8869(03)00162-4

Tkach I, Bechar A, Edan Y (2011) Switching Between Collaboration Levels in a Human–Robot

Target Recognition System. IEEE Trans Syst Man, Cybern Part C 41:955–967. doi: 10.1109/TSMCC.2011.2119480

Tsarouchi P, Matthaiakis A-S, Makris S, Chryssolouris G (2016a) On a human-robot collaboration in an assembly cell. Int J Comput Integr Manuf 3052:1–10. doi: 10.1080/0951192X.2016.1187297

Tsarouchi P, Spiliotopoulos J, Michalos G, et al (2016b) A Decision Making Framework for Human Robot Collaborative Workplace Generation. Procedia CIRP 44:228–232. doi: 10.1016/j.procir.2016.02.103

Unhelkar V V., Siu HC, Shah J a. (2014) Comparative performance of human and mobile robotic assistants in collaborative fetch-and-deliver tasks. Proc 2014 ACM/IEEE Int Conf Human-robot Interact - HRI '14 82–89. doi: 10.1145/2559636.2559655

Vesper C, van der Wel RPRD, Knoblich G, Sebanz N (2013) Are you ready to jump? Predictive mechanisms in interpersonal coordination. J Exp Psychol Hum Percept Perform 39:48–61. doi: 10.1037/a0028066

Vesper C, van der Wel RPRD, Knoblich G, Sebanz N (2011) Making oneself predictable: reduced temporal variability facilitates joint action coordination. Exp Brain Res 211:517–530. doi: 10.1007/s00221-011-2706-z

Wang X, Shi Z, Zhang F, Wang Y (2015) Dynamic real-time scheduling for human-agent collaboration systems based on mutual trust. Cyber-Physical Syst 1–15. doi: 10.1080/23335777.2015.1056755

Wilcox R, Nikolaidis S, Shah J (2012) Optimization of Temporal Dynamics for Adaptive Human-Robot Interaction in Assembly Manufacturing. In: Proc. Int. Conf. on Robotics, Science and Systems.

Wilhelm WE, Zhu X (2009) Enabling flexibility on a dual head placement machine by optimizing platform-tray-feeder picking operations. Flex Serv Manuf J 21:1–30. doi: 10.1007/s10696-010-9059-y

Zanchettin AM, Ceriani NM, Rocco P, et al (2016) Safety in Human-Robot Collaborative Manufacturing Environments: Metrics and Control. IEEE Trans Autom Sci Eng 13:882–893. doi: 10.1109/TASE.2015.2412256

Zheng M, Moon AjJ, Croft EA, Meng MQH (2015) Impacts of Robot Head Gaze on Robot-to-Human Handovers. Int J Soc Robot 7:783–798. doi: 10.1007/s12369-015-0305-z