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Collaborative robotics for improving workplace ergonomics: a case study in the automotive industry

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Doctoral Thesis
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Work carried out under the supervision of
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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration.

I further declare that I have fully acknowledged the Code of Ethical Conduct of the University of Minho.

Robótica colaborativa para melhorar a ergonomia no posto de trabalho: um estudo de caso na indústria automotiva.

Resumo

A quarta revolução industrial desenvolveu sistemas inteligentes, nos quais os robôs colaborativos têm um papel principal. Os trabalhadores sofrem fadiga quando expostos aos fatores de risco que causam as lesões musculoesqueléticas relacionados ao trabalho (WMSD). Como os postos de trabalho manuais muitas vezes conduzem a más posturas e movimentos repetitivos, a implementação de sistemas de Colaboração Humano-Robô (HRC) é frequentemente escolhida como uma solução para melhorar a ergonomia no ambiente de trabalho. O Nível de Colaboração (LoC) significa quais tarefas o robô é capaz de executar como um colega de equipe, o que varia desde o Nível 0 ao Nível 4. Os fatores físicos, cognitivos e organizacionais interagem diretamente em questões relacionadas com as relações laborais em sistemas complexos. Dependendo do LoC para executar uma tarefa, esperam-se diferentes cargas de trabalho físicas e mentais sobre o ser humano. A Dinâmica de Sistemas (SD) é um método para abordar tais problemas com uma visão sistêmica, modelando, simulando e ajudando a tomada de decisões. Investigações prévias sobre postos de trabalho HRC não qualificam e quantificam os riscos ergonômicos variando com o LoC. Por isso, esta tese propõe um modelo de simulação computacional como parte de uma estrutura para tomada de decisões com objetivos de produtividade e redução do risco de WMSD ao implementar um HRC. Além disso, foi realizado um estudo de caso em um posto de trabalho para comparar resultados com as simulações computacionais. Foi escolhido o tempo de ciclo para medir a produtividade, o método ergonômico Rapid Upper Limb Assessment (RULA) para a avaliação da carga de trabalho físico, e o questionário NASA Task Load Index (NASA-TLX) para a avaliação da carga de trabalho mental. Os resultados mostram que a produtividade aumentou mais de 20% em média, as posturas e a carga de trabalho global melhoraram tanto em simulações computacionais como em simulações reais. Também indica que um LoC mais elevado não garante os melhores resultados em termos de produtividade e ergonomia. A conclusão foi que a estrutura para tomada de decisões baseada em SD, que também inclui avaliações técnicas e econômicas, é fundamental para compreender o sistema e obter dados confiáveis. Os trabalhos futuros pretendem desenvolver ainda mais o modelo e aplicar esta estrutura em outras linhas de montagem que considerem a implementação de um sistema HRC.

Palavras-chave: Colaboração Humano-Robô, Dinâmica de Sistemas, Ergonomia, Industria 4.0

Collaborative robotics for improving workplace ergonomics: a case study in the automotive industry.

Abstract

The fourth industrial revolution has seen fast developments in smart systems, in which collaborative robots have a main role. Workers start to fatigue when exposed to Work-related Musculoskeletal Disorders (WMSD) risk factors. As manual handling workstations often lead to awkward postures, repetitive movements and forceful exertions, the implementation of Human-Robot Collaboration (HRC) systems is often chosen as a solution to improve workplace ergonomics. The Level of Collaboration (LoC) means what tasks the robot is capable to perform as a teammate, which varies from Level 0 to Level 4. Physical, cognitive, and organizational factors interact directly on issues related to labor relations in complex systems. Depending on the LoC to perform a task, it is expected different physical and mental workloads over the human being. System Dynamics (SD) is a method to approach such problems with a systemic view by designing, modeling, simulating, and finally making good decisions. Prior research on HRC workstations does not find a solution for qualifying and quantifying ergonomic risks depending on the LoC. Therefore, this thesis proposes a computer simulation model as part of a decision-making framework to achieve productivity goals and to reduce the risk of WMSD when implementing an HRC. Moreover, a case study was conducted in a manual assembly workstation to compare results with the computational simulations. It was chosen cycle time to measure productivity, the ergonomic method Rapid Upper Limb Assessment (RULA) for the physical workload assessment, and the NASA Task Load Index (NASA-TLX) questionnaire for the mental workload assessment. Results show that productivity increased more than 20% on average, postures and the overall workload improved in both computational and real simulations. It also indicates that higher LoC does not guarantee the best results in terms of productivity and ergonomics. The conclusion was that the framework based on system dynamics that also includes technical and economic evaluations is key to understand the system and to make good decisions based on reliable data. Future works intend to further develop the model and to apply this framework in other assembly lines that consider the implementation of an HRC system.

Keywords: Human-Robot Collaboration, System Dynamics, Ergonomics, Industry 4.0

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List of Abbreviations, Initials and Acronyms

ABM	Agent-Based Model
CLD	Causal Loop Diagram
Cobot	Collaborative Robot
DES	Discrete Event Simulation
DHM	Digital Human Modeling
EAWS	Ergonomic Assessment Worksheet
EDA	Electrodermal Activity
EDL	Electrodermal Level
EDR	Electrodermal Response
EE	Energy Expenditure
EMG	Electromyography
EU-OSHA	European Agency for Safety and Health at Work
EWA	Ergonomic Workplace Analysis
FIOH	Finnish Institute of Occupational Health
FMECA	Failure Mode Effect Criticality Analysis
FRAM	Functional Resonance Analysis Method
FTA	Fault Tree Analysis
HFACS	Human Factors Analysis and Classification System
HRC	Human-Robot Collaboration
IEA	International Ergonomics Association
ILO	International Labour Organization
ISO	International Organization for Standardization
KIM-MHO	Key Indicator Method for Manual Handling Operations
LoC	Level of Collaboration
NASA-TLX	NASA Task Load Index
NIOSH	National Institute for Occupational Safety and Health
NMQ	Nordic Musculoskeletal Questionnaire
OCRA	Occupational Repetitive Actions
REBA	Rapid Entire Body Assessment

RMF	Risk Management Framework
RULA	Rapid Upper Limb Assessment
SART	Situation Awareness Rating Technique
SD	System Dynamics
SFM	Stock and Flow Map
SSF	Systematic Search Flow
STAMP	Systems Theoretic Accident Modeling and Processes
SUS	System Usability Scale
SWAT	Subjective Workload Assessment Technique
TAM	Technology Acceptance Model
UX	User Experience
WMSD	Work-related Musculoskeletal Disorders

CHAPTER 1 | Introduction

“Ergonomics is the scientific discipline concerned with the understanding of interactions among humans and other elements. It is the profession that applies theory, principles, data and methods to design in order to optimize human well-being and overall system performance.” (IEA, 2021)

The fourth industrial revolution is characterized by the emerging of new technologies in many fields. As exemplified by Santis, Siciliano, Luca, & Bicchi (2008) and Green, Billinghurst, Chen, & Chase (2008), robots are growing in importance in industrial and nonindustrial fields, such as homes, offices, remote healthcare, agriculture, transport, search and rescue, and space missions. This revolution has the potential to improve the quality of life and well-being at work. However, the presence of robots has social consequences in human environments when interacting with these machines. In industrial environments where robots work alongside humans, it means adjusting behaviors based on both observable human actions and unobservable mental states (Hoffman & Breazeal, 2004).

The interaction of robots with humans aims at improving the quality of human life, to reduce efforts, to increase strength, speed, and accuracy of a wide range of activities. Robots are not aimed at replacing humans completely, as experience and global knowledge are still important factors and difficult to program in any robot.

Recent years have seen fast developments in artificial intelligence, the internet of things, autonomous vehicles, and robotics. Among these smart systems, the collaborative robots (cobots) play a main role by working with humans without barriers in factories (Gervasi, Mastrogiacomo, & Franceschini, 2020). For an efficient system, the workplace must be healthy for the human being, ensuring adequate working conditions.

According to EU-OSHA (2020), Work-related Musculoskeletal Disorders (WMSD) are one of the most common health problems among workers. A good strategy to prevent occupational risks is to implement ergonomic intervention (Petit, Mairiaux, Desarmenien, & Meyer, 2016). Therefore, the implementation of cobots is a usual solution that comes to mind when planning to improve workplace conditions, as it combines robot’s capabilities with human skills aimed at achieving a common goal (Salvendy, 2012). However, it is still complex: to expect increases in productivity at the same time as considering ergonomics; to improve on a punctual problem despite considering the whole system; and to solve an immediate problem safeguarding the evolution of this decision in the future.

A system behaves like a living organism. It may change, adapt, seek goals, respond to events, self-organize, self-preserve, self-repair, be resilient, fight for their own survival and they may even be evolutionary although contain or consist of nonliving things (Meadows, 2008). As stated by Karwowski (2012), the human-centered design requires application of nonlinear dynamics and System Dynamics (SD) is a method to navigate the complex systems. It is grounded in the theory of nonlinear dynamics and feedback control developed in mathematics, physics, and engineering to understand a system's behavior (Sterman, 2004). Through this method it is possible to design, to model, to simulate, to understand and finally to make good decisions in complex systems taking both short and long term into consideration. These systems exist in an environment within boundaries and are characterized by its structure, elements that interact, processes, goals, inputs, and outputs. SD has been applied to address many problems in industry: Industrial risk and accidents (Shire et al., 2018); Ergonomic risks (Abaeian, Inyang, Moselhi, Al-Hussein, & El-Rich, 2016); Psychological risks (Abaeian, Al-Hussein, & Moselhi, 2017); Long-term behavior of the mental workload (Jafari, Zaeri, Jafari, Najafabadi, & Hassanzadeh-Rangi, 2019); Human performance and efficiency (di Nardo, Gallo, Madonna, & Santillo, 2015; Kontogiannis & Malakis, 2019); impacts of human factors in production, on worker low back injury, productivity and quality (Farid & Neumann, 2019); influence of including an extra workstation on physical overload (Mattos, Ariente Neto, Merino, & Forcellini, 2019).

Vensim® is the most used software in SD to model the structure of a system and to simulate its behavior. It analyses variable interactions using a model equation and provides a graphical interface. It supports stocks, flows, causal loop diagrams, delays, queues and stochastic processes generating graphics according to management needs. Modeling is a way to understand the system and speed the learning process in an interactive process between the virtual simulations of the model and the real system reactions.

This thesis proposes exploring the feedback mechanisms when inserting an industrial HRC system, by considering the nonlinear characteristic of the system's behavior. The model is based on SD including physical and mental workloads, as well as the different Levels of Collaboration (LoC) of the robotic system to achieve productivity goals. Therefore, the proposed simulation model is part of a framework to guide managers making good decisions in complex systems. There are frameworks considering physical workload (Colim et al., 2020), or both physical and psychological levels (Sadrfaridpour, Saeidi, & Wang, 2016). Also, an agent-based model considering how ergonomics affects performance (Sammarco, Fruggiero, Neumann, & Lambiase, 2014), and a hierarchical model to improve production time and ergonomics for decision-making (Pearce, Mutlu, Shah, & Radwin, 2018a). These frameworks together address the problem of ergonomics, performance and decision-making. However, these works do not consider the complexity of the system, the evolution of an industrial HRC system over the time, and the possibility of implementing a robot with different capabilities. A framework for management should also consider evaluating technically and economically to be useful in practice.

1.1 Problem and Research Questions

Implementing a cobot in a workplace poses many challenges. As a dynamic and non-linear system, HRC workplaces are difficult to predict the system's behavior in the medium and long terms (Saurin & Gonzalez, 2013), particularly when involving ergonomics (Mattos et al., 2019).

There are many researchers dealing with the ergonomic issues with HRC systems (Table 3-1 and Table 3-2). However, prior research on HRC workstations does not offer a solution for qualifying and quantifying ergonomic variables depending on the LoC over time. Therefore, there is a need for addressing the complexity of WMSD in the industry, including both mental and physical workload. Moreover, the problem should consider productivity as it is key for management to implement HRC systems. In addition, predicting the behavior of HRC for different LoC would benefit decision-making.

In order to answer to the research question "How to reduce decision-making uncertainty in the implementation of human-robot collaboration systems?", this work proposes a computer simulation model to support decision-making in an automotive company workstation where a collaborative robot might be implemented to reduce the risk of WMSD. Considering that implementing an industrial HRC system is beneficial for ergonomics and productivity, is there any counterintuitive behavior that can happen in the short- and long-terms when looking at the whole system?

1.2 Objectives

The main objective of the current thesis is to reduce the risk of WMSD by developing a decision-making framework for implementation of HRC systems, which is related to ergonomic factors and productivity, allowing management to choose a collaborative robot that achieves company's needs.

In order to achieve the main goal, specific objectives were considered during the research:

- To review the literature of risk assessment in HRC systems.
- To establish the factors to be considered and how they interact.
- To design a conceptual diagram that represents the HRC workplace.
- To develop a detailed model to understand the feedback mechanisms.
- To predict the system's behavior over time.
- To evaluate the results in implementing collaborative robots regarding productivity and WMSD risk.

1.3 Thesis Structure

The current thesis is structured in 9 chapters based on publications in books, proceedings and scientific journals. As the thesis evolved, some chapters became outputs for the project "Factory of the Future: Smart Manufacturing", in which the author was involved.

Therefore, and for simplification purposes, this thesis' structure is based on the manuscripts that were already published and, accordingly, the corresponding chapters were organized and formatted in the same way of the papers that were published before. Additionally, and with the aim of the coherence of the text format, some chapters were slightly adapted/changed in comparison with the published papers.

Chapter 1 introduces the thesis with contextualization, an overall picture of the main topics of this work, the problem to be addressed, the research questions and the objectives.

Chapter 2 is an introduction to the concepts of system dynamics. It presents systems thinking as a possible approach for complex system by bringing examples in which ergonomics and collaborative robots were modeled. Finally, it compares the benefits of a decision-making based on the results simulated in a computational model over conclusions of a mental model.

Chapter 3 is a literature review of risk assessment in HRC systems. It presents the empirical studies from the last five years, in which methods and techniques were used to assess ergonomics in HRC systems. In total, 67 papers were considered for a preliminary overview, of which 23 were included in the portfolio for analysis. The physical risk assessment was discussed in terms of communication between human and robot, and mental risk assessment was analyzed though studies that applied NASA-TLX questionnaire. The metrics used to assess physical and mental workloads are discussed showing the emerging research fields.

Chapter 4 presents a system dynamics-based model for designing feedback mechanisms related to ergonomics and productivity in HRC systems. Based on the literature, it defines the factors to be considered and how they interact to predict the behavior of the HRC system over time. The result is a qualitative model (Causal Loop Diagram), in which the system is formalized and delimited in the context of HRC workplaces. The final result is to be modeled for computer simulations in order to quantify prospected scenarios and predict system's behavior over time.

Chapter 5 presents a detailed model with a quantitative approach to the problem of absenteeism due to WMSD in an HRC system. It prospects scenarios generated by computer simulation in order to predict the best working condition between worker and robot. Graphic results show the evolution of sick leave and productivity over time for different LoC.

Chapter 6 presents a framework together with a case study that deals with the problem of successfully implement an industrial HRC system. Ergonomic methods (RULA and NASA-TLX) were applied in a manual assembly workstation and its results were used as input for an SD model. Technical, ergonomic and economic evaluations follow the prospected scenarios and drastically reduces the risk management in decision-making.

Chapter 7 presents the simulation of a human-robot interaction involving the worker in the process of implementing a new HRC system, as well as quantifying productivity, physical and mental workloads. A replica of a current workstation was compared with a scenario where a human hand simulates the tasks performed by a robot arm. Results indicated which organizational changes should be implemented and which LoC would be preferred in the specific workstation.

Chapter 8 discusses the results in the light of the research questions and objectives. It shows that the decision-making framework and the computational model based on system dynamics advance the understanding of ergonomic interventions.

Chapter 9 summarizes the main conclusions of this research and suggests future works.

The thesis's structure is presented in Figure 1-1, in which the publications are highlighted in blue, as follows:

- Borges, G.D., Carneiro, P., and Arezes, P. (2022). Systems thinking in industry 4.0: ergonomics and collaborative robotics. Accepted for publication as book chapter in "Ergonomia do Trabalho na Indústria 4.0 – Desafios & Aplicações". Editora UFSC.

- Borges, G.D., Cardoso, A., Gonçalves, H., Colim, A., Carneiro, P., Arezes, P. (2022). Physical and Mental Workload Assessment in Human-Robot Collaboration Workplaces – a Review. Proceedings of the 4th International Conference on Human Systems Engineering and Design (IHSED 2021). http://doi.org/10.54941/ahfe1001155

- Borges, G.D., Carneiro, P., and Arezes, P. (2022). Human Factors Effects on a Human-Robot Collaboration System: a Modelling Approach. Proceedings of the 21st Congress of the International Ergonomics Association. IEA 2021. LNNS, 223, 829-838. Springer, Cham. https://doi.org/10.1007/978-3-030-74614-8_102

- Borges, G.D., Ariente Neto, R., Mattos, D.L., Merino, E., Carneiro, P., and Arezes, P. (2021). A Computational Assessment of Ergonomics in an Industrial Human-Robot Collaboration Workplace Using System Dynamics. Advances in Human Factors in Robots, Unmanned Systems and Cybersecurity. AHFE 2021. LNNS, 268, 60-68. Springer, Cham. https://doi.org/10.1007/978-3-030-79997-7_8

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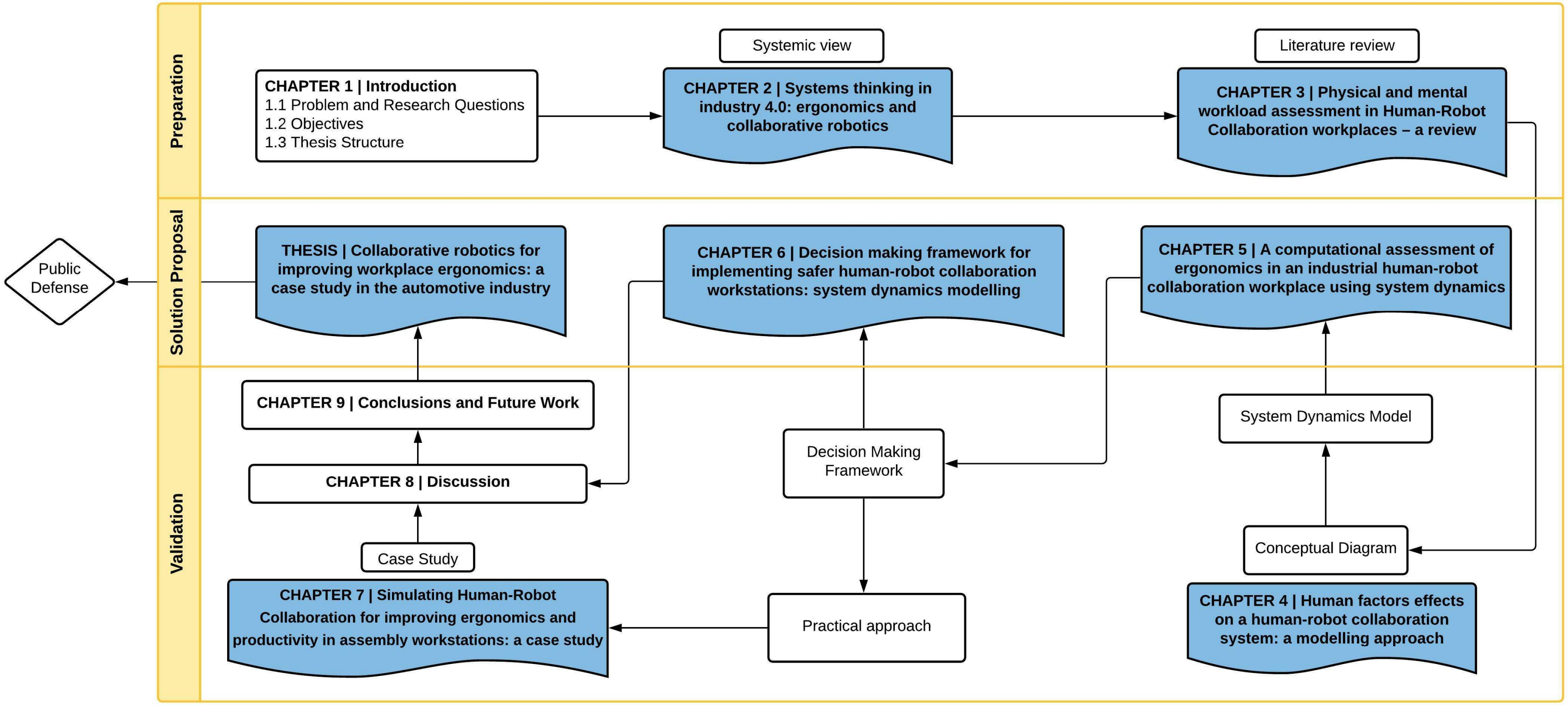

Figure 1-1. Thesis' Structure.

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CHAPTER 2 | Systems thinking in industry 4.0: a new paradigm in ergonomics and collaborative robotics

Abstract. An HRC workplace is a complex system, in which all ergonomic domains are present. Since systems thinking considers the factors and interactions that contribute to an outcome, the aim of this chapter is to introduce the concepts of System Dynamics (SD) as a possible approach. First, it presents an HRC workplace in the industry and what to take into account when designing such workstations. Second, the steps to create an SD model are explained along with its symbols, structures, and diagrams. Finally, it presents some researches that considered ergonomics and collaborative robotics. As a conclusion, it shows the benefits of a decision-making process based on qualitative and quantitative information on a computational model simulation.

“Realize that everything connects to everything else.” (Leonardo da Vinci)

2.1 Introduction

The industry is advancing rapidly thanks to Industry 4.0 technologies. The newly developed systems have solved old problems in ergonomics and productivity, but the working environments are becoming more complex and harder to comprehend. Nowadays, it seems possible to obtain the best outcome of opposite sides: to increase production targets meeting ergonomic needs, to develop solutions for punctual problems considering the whole system and its dynamics, and to solve today’s urgent problems without having to deal with new (or the same) problems in the future. Among countless applications, HRC has been used to reduce workplace injuries and to increase production at the same time by combining capabilities from both humans and robots in an almost-perfect and long-lasting relationship. However, the main challenge behind successfully implementing an HRC industrial system is the fact that classical methods cannot foresee non-linear behaviors of complex systems, since the latter produces counter-intuitive effects most of the time. In this context, SD presents itself as a paradigm shift, a tool capable of handling all the aforementioned demands inside a controlled environment of computer simulation.

2.1.1 Collaborative workplace in the industry 4.0

A workplace designed for HRC should seek to optimize the allocation of tasks. Therefore, the robot will be responsible for activities that require strength, precision, speed, and repeatability, since the robot is fatigue free. For the human will remain the tasks that add value and depend on cognitive processes and adaptability. From a social point of view, HRC is an interaction where the worker and the robot exchange information to achieve the same goal, but performing independent subtasks, in which one needs to trust the other and both learn and adapt in the process (Bütepage & Kragic, 2017).

An example of an HRC job is shown in Figure 2-1, in which Petruck et al. (2019) designed a manual assembly workstation with the possibility of assembling different products on a production line. The parts are transferred by the robot from the production line to the worker's table, where manual assemblies are carried out, and then are transferred again by the robot to the production line. The robot is attached to a structure above the height of the worker, so that they work together, but in safety, and without movement restrictions. This is a very efficient solution for application on production lines in several industries.

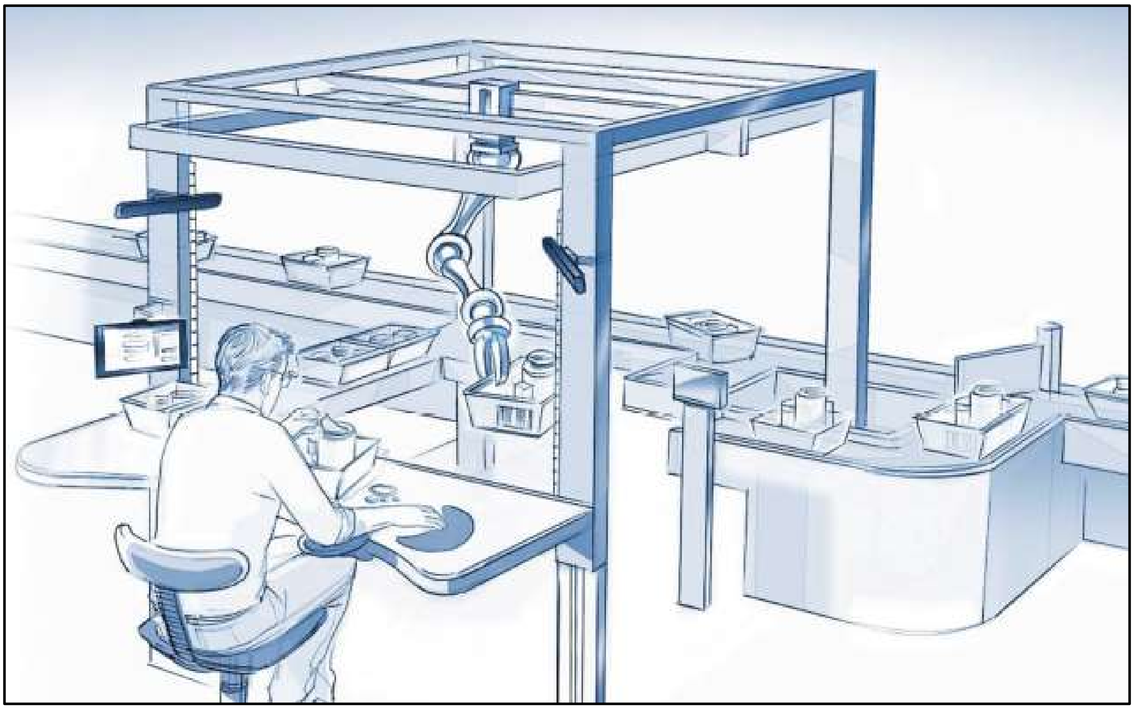

Figure 2-1. Vision for human-robot collaboration in multi-variant production.
Source: Petruck et al. (2019).

The robot can collaborate at different levels, depending on the technology available and the task to be performed. Figure 2-2 exemplifies each of the possibilities, but it is important to note that higher levels of automation do not necessarily guarantee higher levels of productivity, safety, or operator well-being. Higher levels of collaboration can even induce problems such as confusion or loss of certain skills (Lagu & Landry, 2011). However, certainly the closer human and robot work, the better their communication and system safety settings must be.

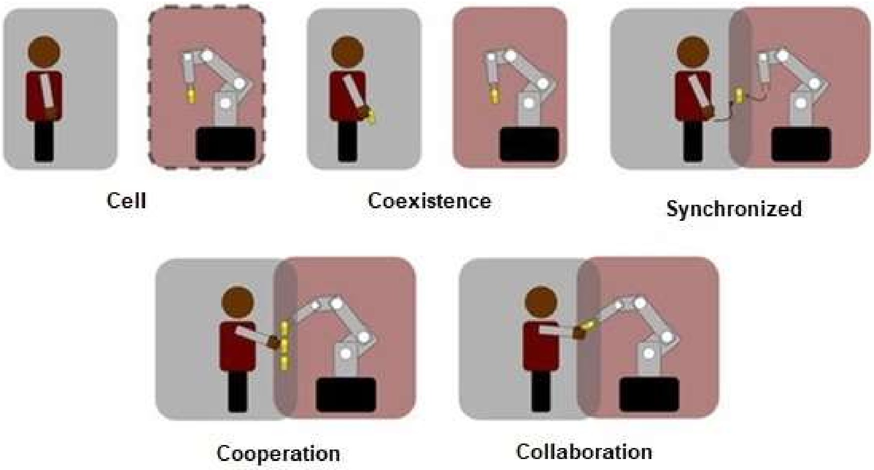

Figure 2-2. Levels of collaboration between a human worker and a robot.
Source: Olivares-Alarcos, Foix, & Alenyà (2019)

2.1.2 Design of a Human-Robot Collaboration workstation

When designing an HRC workstation, the objectives and the following system variables must be considered:

→ Human - posture, strength, biomechanics and cognition.
→ Robot - joints, position, speed, acceleration and sensors.
→ Human-robot interaction - strength and feedback strength.
→ Process - production goals such as cycle time and quality.

From an ergonomic point of view, a workstation must allow different postures for the worker, as there is no posture considered ideal that can be sustained for long periods. The most productive solution during an assembly task with a robot requires that the working posture is adaptable for both standing and sitting positions. This means that the worker can choose at any time the position in which he prefers to perform the task. Regarding the dimensioning of the workstation, it is important to note that the anthropometric databases are not sufficient. These measurements present only information regarding static characteristics in normalized postures, and do not report on ranges and movements for specific tasks, especially in an HRC system. Not considering ergonomic aspects can generate undesirable effects such as fatigue, musculoskeletal complaints, monotony, and reduced performance.

Psychological factors should also be considered when planning an HRC workplace environment. In order to increase worker confidence and motivation, it is important to provide empowerment and training. For example, if the human has the power to guide the robot so that it appears to have control over the machine, it can have the psychological effect of perceiving the robot as a helper. A training program enables workers to understand the capabilities and limitations of the robot to develop a more realistic mental model of the system, with expectations set correctly. The result is that the worker, with the accumulation of knowledge and confidence, begins to identify problems, solve robot failures and understand the reasons that led to this. As explained by Sadrfaridpour et al. (2016), trust is a critical element in HRC because it directly influences the degree of autonomy that the human delegates to the robot, which determines the efficiency and, finally, the quality of the processes.

2.2 Systemic Thinking

The HRC workplace can be interpreted as a complex system, where a diverse set of variables is present. From the ergonomic perspective, all physical, cognitive, and organizational domains play a part and influence the system simultaneously in different ways. It is worth remembering that a system is composed of its elements (people, equipment, environmental conditions), its interconnections, and its function.

In complex systems, it is common to try to solve a problem and the solution ends up creating a new problem (Sterman, 2004). Sometimes, when being modified, the system reinvents itself or responds unpredictably due to the reaction of other system elements that aim to reestablish the status quo. This is the essence of complex systems. However, as the knowledge about the system broadens, it is possible to make better decisions and to intervene adequately.

The chaos theory, developed by Lorenz (1963), established the theoretical basis of climate and weather forecasts. Lorenz became well-known around the world along with his quote “Does the flap of a butterfly’s wings in Brazil set off a tornado in Texas?” that gave birth to the term ‘Butterfly Effect’. Lorenz affirms that deterministic chaos is when the present determines the future, but the approximate present does not determine the future approximately. In other words, the deterministic nature of a system does not imply its predictability. This means that such complex systems display hypersensitivity to initial conditions, and precise long-term predictions are not always possible in some systems, even when the initial conditions are well-bounded.

To understand a system is to know how to identify all its important parts and how they relate to one another over time. Therefore, computational models are used to simulate and foresee complex system's behavior in multiple scenarios. The computational model's objective is to increase the knowledge about the system and not necessarily to predict the future.

Human-machine systems are considered complex and are characterized by their structure, interacting elements, processes, goals, inputs, and outputs. In his Ph.D. thesis, Tang (2016) presents the influential factors in the HRC system, which are represented in Figure 2-3. The author affirms that "those at the wider system level can be influenced by environmental factors and changes made at the system but they are ungovernable elements, and therefore it is decided the appropriate level to address the issue in human-robot collaboration is at the system level".

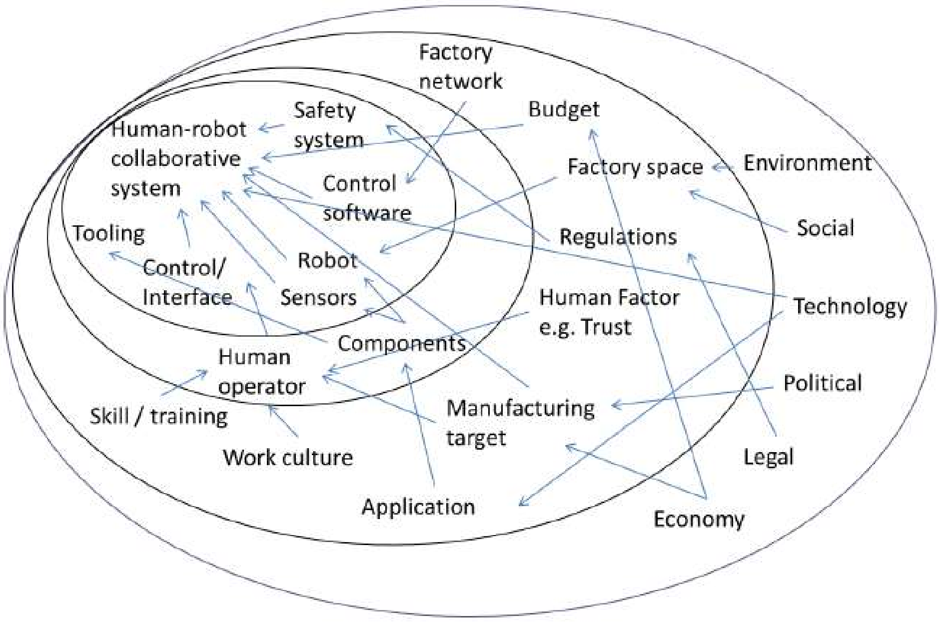

Figure 2-3. Human-robot collaborative system and its influential factors.
Source: Tang (2016).

2.3 Systems Dynamics

The Systems Dynamics (SD) is based on the theory of non-linear dynamics and feedback control developed in mathematics, physics, and engineering. The modeling is grounded in systemic thinking, which, as a holistic approach, takes into consideration feedback and delays to learn about the system's behavior (Sterman, 2004). SD is a methodology to navigate complex systems. With this method, it is possible to project, model, simulate and comprehend complex systems, which provides enough information for better decision-making when considering both short and long terms. It is important to consider the two timeframes because, when analyzing only the short-term scenario, it is possible to take decisions that would not agree with the expected long-term results.

Therefore, this methodology envisages future scenarios through simulation and builds up knowledge about the system's behavior to better understand reality and make more resilient decisions. Within the industrial dynamic, in the 1950s, Jay Forrester funded the Systems Dynamic Group at the Massachusetts Institute of Technology (MIT) in the USA. Forrester claims that our ability or instinct to understand dynamic changes is limited to simpler scenarios where cause and effect exist and are closely linked to each other. For more complex scenarios and non-linear effects, such instinct is useless. Hence, dynamic systems deal with causal interactions between variables in a complex system's structure. By modeling the system, it is possible to analyze the dynamic behavior depicting interactions, feedbacks, and changes over time.

The method of system dynamics is used in a wide variety of problems and areas such as health systems, economics, sustainable development, and urban mobility. In the industrial sector, the use of the non-linear dynamic systems theory can be employed to approach the HRC system's features. In a productive man-machine system, the priority when including a robot in the system is human safety. When addressing the whole system, it is possible to explain non-linear interactions and feedback structures, which classical methods cannot handle when applied to examine causes and effects of events. Very often, workers are made responsible for causing accidents when they are described sequentially. However, it is important to know the circumstances and the system mechanism in order to forestall accidents, given complexity-caused incidents and poorly understood conditions are usually attributed to human errors (Johnson, 1980).

2.3.1 Sequential Models

Accidents are a serious problem in the industry and several methodologies have been put in place to reduce the number of working accidents. The classic approach consists of using sequential models that present a linear succession of events linked by cause and effect. The most used sequential models are HAZOP - Hazard and Operability Study (Kletz, 1999), FTA - Fault Tree Analysis (Watson, 1961) e FMEA / FMECA - Failure Mode Effect Criticality Analysis (Standard, 1980). According to Bouloiz et al. (2013), these sequential models have two main drawbacks.

First, they do not consider the interactions among system components, and second, they do not address the human and organizational factors appropriately. On the other hand, systems dynamics show that industrial accidents emerge from interactions within the system and not only from a sequence of events that are connected by cause and effect.

2.3.2 Risk Analysis Models

Among sequential models, some risk analysis models are frequently used in industrial safety reports. The following methods are non-linear and, therefore, successful in the treatment of complex interactions between system components that can cause accidents: RMF - Risk Management Framework (Rasmussen, 1997), HFACS - Human Factors Analysis and Classification System (Shappell & Wiegmann, 2000), FRAM - Functional Resonance Analysis Method (Hollnagel & Linköping, 2004) and STAMP - Systems Theoretic Accident Modeling and Processes (Leveson, 2004). According to Shire et al. (2018), these methods can enhance the understanding of risk and the whole system, but they lack providing support to the decision-making process of dynamic risk, a limitation that can be overcome by System Dynamics. Due to its characteristics, the system dynamics can be applied to:

→ Analyze accidents in retrospective and evaluate risks preventively.
→ Present complex models in a comprehensive visual display.
→ Provide a perspective on the problem's structure based on the availability of limited data.
→ Model uncertainty by undertaking sensitivity analysis, testing, and interpreting the qualitative mode of behavior.

2.3.3 Simulation Techniques

As presented by Nance (1996), there are three types of simulation: Discrete events (the nature of the state change and the moment in which the change happens both require a precise description); Continuous (equations models that do not result in discontinuities); Monte Carlo (uncertainty models that do not represent time because their goal is to satisfy the relationships of the deterministic problem through a stochastic process).

In the book "The Big Book of Simulation Modeling", Borshchev & Grigoryev (2020) mention that the most frequently used modeling techniques are DES (Discrete Event Simulation) which aims for understanding special events that occur in a system, and ABM (Agent-Based Model) that intends to model changes inside a system as a result of interactions between its individuals. As explained by Farid, Purdy, & Neumann (2019), the system dynamics is more promising because it allows:

→ Modeling and understanding the cause-effect-feedback relations and behaviors within a system.
→ Managers to employ their mental models as a basis for the computational model and to use the platform to test their suppositions about the system.
→ Providing managers with a different understanding and perspective about system's factors and interactions (e.g., between risks of lumbar injuries and performance).

For successful use of SD, Sterman (2004) recommends a few guidelines that are summarized below:

→ Develop a model to solve a particular problem and not only to model the system. This means to exclude all factors that are not relevant to the problem. The objective is to improve the system performance according to the customer's priority.
→ Integrate modeling into a project at the beginning of the definition phase, with a focus on diagnosing the system structure.
→ Make sure that SD is the right technique for the problem. Some other tools and methods can be added. Effective modeling relies on a solid base of data and an understanding of problems.
→ Asking yourself constantly, since the beginning of the project: How will the model help the client to make decisions? How do we get there from here?
→ Begin the test when writing the first equation because each variable must correspond to a significant concept in the real world, verified for dimensional consistency and replication of historical behavior.
→ Modeling is an interactive process where customers must be able to test the model themselves in real-time to suggest and criticize. Models must be tested in extreme conditions to ensure the logic is correct.
→ Validation and confidence come gradually as time passes by constantly confronting the model with data and expert opinion.
→ The model should work as quickly as possible, and details should be added only when necessary. A broad model's boundary is more important than many details. The results of the simulation experiments inform the conceptual understanding and help to increase confidence in the results.
→ Implementation is a long-term process of personal, organizational, and social change.

2.4 Modeling

"Everything should be made as simple as possible, but not simpler." (Albert Einstein)

Everyone has mental models that are simplified means of understanding the world. This is an important tool that shapes our thinking and very useful to make connections between previous and new situations. As it is not possible to store all information and not all information is needed to understand how something works, good models neglect unimportant factors and maintain those that represent essential interactions of the system. In this sense, modeling is a way of understanding the system and streamlining the learning process. Its objective is not to predict what exactly will happen, but to solve real problems in a virtual environment using the same characteristics to which the real world is exposed.

Forrester (1971) says that, in the long history of human evolution, people did not need to understand multiple nonlinear feedback cycles. This means that the natural evolutionary process and the formulated mental models did not give humankind the "mental skills to properly interpret the dynamic behavior of systems of which we have now become a part". This is known as counter-intuitive behavior, and people may experience it when dealing with these complex systems.

In order to create an SD model, Forrester (1961) and Sterman (2004) propose to follow some steps: 1) Find the customer, define the problem, identify the variables and interactions, historical behaviors of key concepts, and time horizon; 2) Describe the variables and the causal relationships between them; 3) Build the causal link diagram that represents feedback mechanisms, to formulate a dynamic hypothesis or theory about the causes of the problem; 4) Build a stock and flow diagram, which introduces the dimension of time in the model and formulates the boundaries of the system; 5) Simulate the model, evaluate long-term behavior of the complex system and test the model until it becomes robust in extreme conditions, sensitive to initial conditions and suitable for the purpose in question; and 6) Design and evaluate improvement policies.

The most used software to simulate system dynamics is Vensim®. It analyzes the interactions of variables using a model equation and provides a graphical interface with stocks, flows, and causal link diagrams. It also supports delays, queues, and stochastic processes generating graphics according to needs. The software is owned by Ventana Systems.

2.4.1. Problem definition

According to Sterman (2004), modeling is an interactive process between the model virtual simulations and the real responses of the system. The client is the people to be influenced and whose behavior must change for the problem to be solved. Consequently, it is paramount to model according to the client's abilities and objectives. To start a model, it is mandatory to have a problem and a visual unwanted trend, e.g., in a chart. The objective, therefore, is to implement changes to alter the curve's trend, causing it to stabilize at the desired level in a set period.

Once the problem and objectives are defined, it is necessary to name the elements that will be present to mirror the logic by which it is possible to understand the real world. It is also important to interview different people to acquire useful data when formulating a model. The reason to do so is that, very often, variables that do not change the dynamics of the system a priori can influence it as the system evolves.

The interactions between variables can be described through formulas, statistical behaviors of similar studies or historical behaviors of the system itself, and the experience of those who already work in the area. The Vensim® software can be used to design the causal link diagram, from which stocks, flows, and the equations that govern the system variables are defined.

2.4.2. System structure

"The structure consists of feedback cycles, stocks, flows and non-linearities created by the interaction of the physical and institutional structure of the system with decision-making processes of agents who work on it" (Sterman, 2004).

The cause-and-effect interactions between variables are related by causal links, shown by arrows in Figure 2-4. The positive polarity (+) should be read as "if X increases, then Y increases" and the negative polarity (-) should be read as "if X increases, then Y decreases".

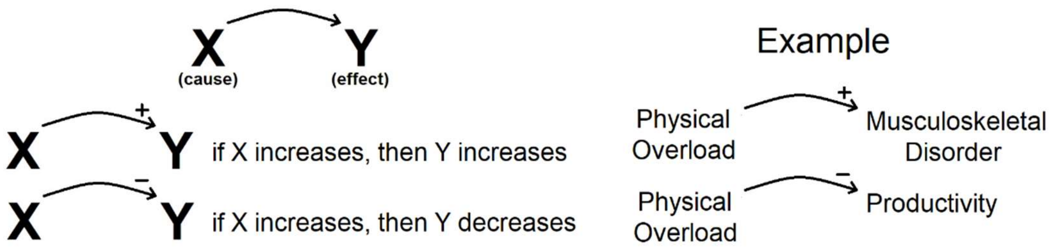

Figure 2-4. Causal links between variables.
Source: Author (adapted from Sterman (2004).

A holistic view of complex systems shows that changes in the variables can generate reactions. A cycle means that the ‘effect’ directly or indirectly influences the ‘cause’. In Figure 2-5, the reinforcement (R), or positive cycle, should be interpreted as “if X increases, then Y increases, then X increase even more due to Y” and the balance (B), or negative cycle, should be interpreted as "If X increases, then Y increases, but then X decrease due to Y".

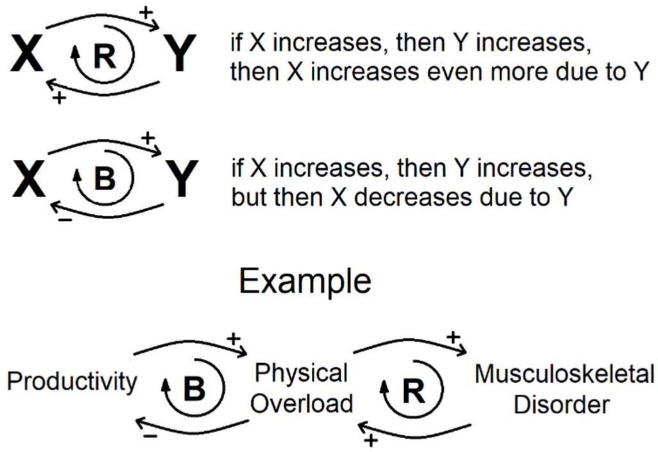

Figure 2-5. Positive and negative feedback loops.
Source: Author (adapted from Sterman (2004).

Causal Link Diagram – is a method to represent the relationship between pairs of elements and to recognize feedback structures. It has a qualitative aspect and quickly captures the hypotheses about the dynamics’ causes, selects the mental models of individuals and teams, and communicates important feedbacks that are responsible for the problem. It can be very useful for drawing the diagram, but it does not capture the stock and flow system structure. Stock and flows in conjunction with feedback are the central concepts of systems dynamics theory (Sterman, 2004). Stocks are accumulations that give inertia to systems and provide them with memory as they accumulate past events. Flows change the value of stocks. Stocks create delays by accumulating the difference between the inflow and the outflow. Figure 2-6 exemplifies this logic.

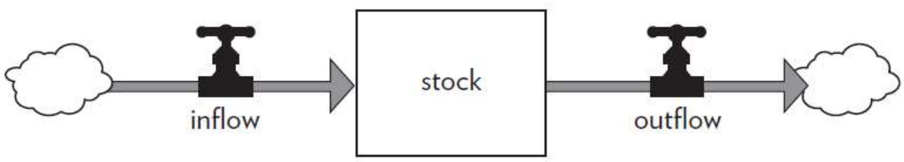

Figure 2-6. Example of stock and flow.
Source: Meadows (2008).

In a system, stocks are usually important variables employed to inform decision makers about their position, providing them with the information they need to act. Inflow and outflows may differ in a process due to stocks, which absorb the difference. This is the standard situation whenever two activities connected to one stock are controlled by different decision makers, involve different resources, and are subject to different requirements (Sterman, 2004).

For example, in a boxing process: the input is the rate at which the product is received, and the output is the rate the product is placed in a box, where the stock is the material in transit.

$$Stock(t) = \int [Inflow(t) - Outflow(t)]dt + Stock(0)$$

Delay is the time between receipt and delivery.

$$Outflow(t) = Inflow(t - Average\ Delay\ Time)$$

Stock and Flow Map - is a method that uses differential equations to create the system dynamics model and generate information for decision-making. It has a quantitative aspect, where auxiliary variables (including exogenous inputs) are used to define some intermediate concepts and are convenient to explain, understand, and modify a model more easily. In Figure 2-7, auxiliary variables are “coffee intake” and “discrepancy”. The “desired energy level” is an exogenous input to the system.

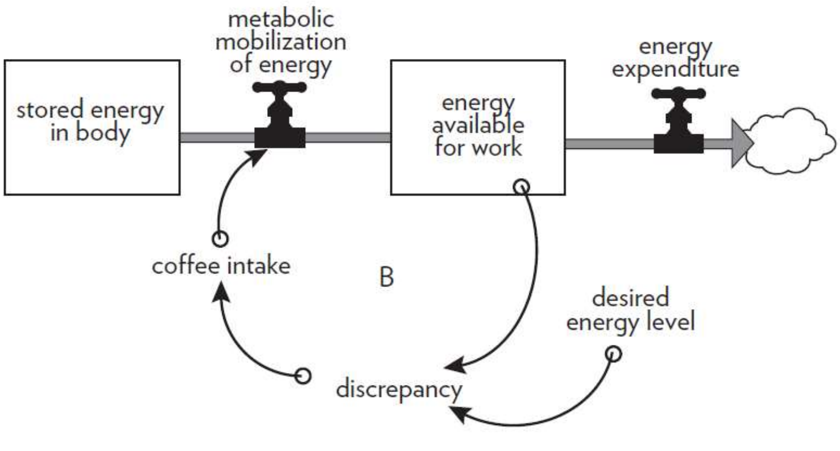

Figure 2-7. Example of Stock and Flow Map.
Source: Meadows (2008).

2.4.3 Behavior

"Quite literally feedback is behavior – we know nothing of our own behavior but the feedback effects of our own outputs" (Powers, 1973).

System behavior emerges from its structure and the real power of the SD is in simulation. As explained earlier, stocks are important variables to be controlled via charts that are developed by equations that interconnect variables. The three fundamental patterns of stock behavior are shown in Figure 2-8, namely exponential growth (positive feedback), asymptote (negative feedback), and oscillation (negative feedback with delays). More complex modes result from non-linear interactions between them (Sterman, 2004).

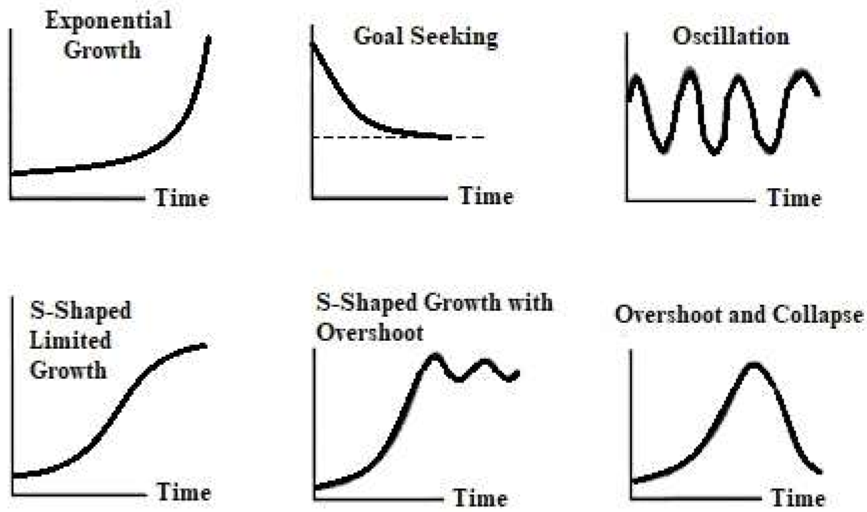

Figure 2-8. Common modes of behavior in dynamic systems.
Source: Sterman (2004).

A system changes constantly, and even the most stable one will change over a long period. This complex behavior appears due to the dynamic nature of non-linearity and the strong interaction between the system components. Some system behaviors make them look like living and intelligent organizations (Sterman, 2004) as follows:

→ Self-organization and adaptability - The dynamics of a system emerge from its internal structure. Some rules and skills can change and even allow its own selection and multiplication as they evolve.

→ Management by feedback - The results of our actions define the situation we will face in the future and this new situation modifies our evaluation of the problem and the decisions we will make. As the decisions made cause a change and trigger other components of the system, other reactions may return to us.

→ Contradiction to intuition- Our intuition is based on accumulated knowledge and experience. In complex systems, however, the causes and effects can be different from each other in time and space contexts. Individuals search for reasons for the events they are trying to explain in the events' periphery. When intuition fails, it is important to simulate on a computer and see how the model behaves itself. For example, time delay feedbacks provide different responses in the short and long term.

→ Resistance to policies - The complexity of the system we work on can reduce our ability to understand the full range of feedbacks that operate on the system. After all, many obvious solutions fail and even make the situation worse because our actions trigger side effects. What we call an unforeseen side effect can be understood as a sign that cause and effect may be distant in time and space and the grasp about the system is not complete.

2.4.4 Model Simulation and Validation

Once the entire system is built and its formulas are implemented in the Vensim® software, it is possible to draw results from the simulation. The resulting charts show the relationships between variables over time, and there are different methods of validating the model as follows: structure test, limit test, sensitivity test, dimension check, parameter check, reality check, extreme conditions analysis, and structurally oriented behavior test to validate stock and flow diagrams (Jafari et al., 2019; Sterman, 2004).

The sensitivity analysis is especially important to learn from the model. By applying it, one can increase awareness about the relationship between the structure and behavior of complex dynamic systems, besides testing the conclusions' robustness on the uncertainty related to estimated parameters (Sterman, 2004). Therefore, it is important to choose parameters that strongly affect the system behavior and the most accurate data in order to decrease uncertainty.

However, it must be understood that, by definition, even a robust model does not represent reality faithfully. Although testing is essential, a complete model validation is impossible. And yet, either way, managers will use a model to make decisions. The fact is that a manager does not choose whether to use a model or not, but rather which model to use:

→ Mental model based on experiences and intuition.
→ Computer simulation model where it is possible to visualize, understand, learn, perform calculations, simulate, evaluate feedback cycles, and predict counter-intuitive behaviors.

2.4.5 Policies for system improvement

Once the model has become reliable in terms of structure and behavior, it is time to evaluate policies for system improvement. Policy design includes the creation of strategies, structures, and rules in the decision-making process of those that will eventually interfere with the system.

A Policy Structure Diagram is a conceptual map of the decision-making process that is embedded in the organization. It conveys information used by modelers that is allegedly used by decision makers to control the system flow rates and the delay involved in specific decisions.

As mentioned before, cause and effect can be far apart in time and space, so it is imperative to correctly define the system's time horizon and limits. Since the choice of the time horizon can dramatically influence policy evaluation, a good rule of thumb is to set the time horizon as several times the longest time delay (season, fiscal year, elections). Moreover, to avoid resistance to policies, it is necessary to expand the limitations of our mental models. Forasmuch as the decisions we make always create feedbacks, we need to understand their implications (Sterman, 2004).

2.5 System dynamics in collaborative robotics and ergonomics

According to Lorenzini, Kim, Momi, & Ajoudani (2019), the two main requirements to avoid work injuries are models to estimate the cumulative fatigue due to repetitive working load, and methods to mitigate its negative effects. Recently, interest in this topic has been increasing. As affirmed by Karsh, Waterson, & Holden (2014), the ergonomic study must always involve a systemic perspective in which any analysis or intervention considers the context as a whole.

Mattos et al. (2019) studied the physical overload of workers in the production line and how this overload can occur in a complex system. They perform a quantitative evaluation in order to approach ergonomics issues in industrial environments. In this work, causal link and stock and flow diagrams are presented, in addition to the formulas used in the model simulation.

2.5.1 Collaborative robotics

The objective of an HRC system is to increase productivity and efficiency while improving ergonomics and quality by allocating the most suitable tasks for humans and robots. It must be taken into account that cause and effect in complex systems, such as HRC, are often apart in time and space. To illustrate how counterintuitive a behavior can be, Kontogiannis & Malakis (2019) exemplify how short and long term impacts of a technical solution can be different: "Automation can increase productivity now, but overconfidence can lead to other mistakes in the long run; a modern control room can facilitate serial information digitization but prevent parallel information processing that is spread across different pages of visual display units." Another curious example is presented by Challenger, Leach, Stride, & Clegg (2012): "When individuals are underperforming, counter-intuitive management strategies can be beneficial, for example, by reducing supervisory control, allowing changes in the content of work, potentially resulting in better performance."

In this context, some questions may be raised when including a robot to share a workstation with humans. Is there any counter-intuitive behavior that can happen when looking at the entire system? Is there something hidden behind positive expectations? How will the system react to this? Is avoiding accidents and repetitive movements sufficient to achieve a healthy work environment? As pointed out by Dulac & Leveson (2004), although decisions may seem safe and reasonable within the individual work environment and local pressures, they can interact in unexpected ways and cause accidents when all system operations are considered.

Because of the aforementioned reasons, the SD method is adequate for addressing the complex, and sometimes chaotic, HRC system.

2.5.2 Ergonomics

To have a worker in conventional production lines in the industry figures as a great ergonomic challenge. According to Karwowski (2012), the design of the human-centered workplace requires the application of theories of nonlinear dynamics, and there are many variables to be taken into account in a complex system that changes over time. Stergiou (2016) states that nonlinear dynamics can be used to examine the inherent variability of human motor performance that happens in several task repetitions, e.g., the variability of human muscle activities. Another study by Abaeian et al. (2016) also concluded that modeling the system dynamics not only provides a graphic illustration, showing the logical links between cause and effects, but also increases the knowledge of how ergonomic risk can evolve during the execution of tasks.

Additionally, not only the physical aspects of ergonomics, but also organizational and cognitive aspects are present in such systems. Jafari et al. (2019) simulated the dynamic mental workload mechanism and its interaction with task demand and resource supply variables. He concluded that dynamic models were useful to analyze the long-term behavior of mental workload by considering several components and associated uncertainty. According to Scerbo (2000), ergonomics professionals can help to establish proper displays and representations of concepts toward more intuitive models.

According to Charalambous et al. (2016), manufacturing industries often fail to implement HRC systems because they lack understanding about related human and social issues. To ensure the acceptance and effective use of robots, it is critical to understand human factors and their dynamics.

Several studies have already addressed the system dynamics factors in the ergonomics field. Abaeian, Inyang, Moselhi, Al-Hussein, & El-Rich (2016) illustrate how ergonomic risks can lead to work-related musculoskeletal injuries in a task of residential construction. During the following year, the same authors Abaeian, Al-Hussein, & Moselhi (2017) present a list of psychological risks based on the literature. And Jafari, Zaeri, Jafari, Najafabadi, & Hassanzadeh-Rangi (2019) present a dynamic model that can be used to analyze the long-term behavior of mental workload. Other studies have also focused on factors that influence human performance and efficiency (di Nardo et al., 2015; Kontogiannis & Malakis, 2019). In the work carried out by Farid & Neumann (2019), the authors modeled the impacts of human factors on production, on the lumbar injury of the worker, on productivity, and quality performance. Mattos, Ariente Neto, Merino, & Forcellini (2019) simulated the “performance of a production line balanced against physical overload by the addition of an extra workstation” in a plan for automotive electrical components in Brazil. The simulation concluded that reducing the physical workload allows the workforce control grid to govern the entire system, which produces better results.

2.6 Decision-making

“All decisions take place in the context of feedback loops.” (Forrester, 1961)

In any system where humans are present, information is converted into decisions and, therefore, the model’s structure consists of how the decision-making processes occur. According to Leveson (2004), the main causes of accidents in complex socio-technical systems are decision-making related.

The literature review conducted by Shire et al. (2018) states that “Given the results obtained, the authors were able to improve safety through better decision-making by including previous behavioral events in modeling structures to create effective safety policies, performing system analysis, as well as applying a holistic approach to analyze the causes of accidents beyond human error. In circumstances where the actions, omissions, communications, or policies of senior management directly or indirectly affect the supervisory practices, actions, or conditions of the operator(s) and lead to human error, control failure, or unsafe situation, Systems Dynamics has often been used as a tool to identify factors responsible for accidents.”

The framework presented by Bouloiz et al. (2013) proposes an integrated structure for modeling safety conditions in an industrial system to support decision-making. It was concluded that management practices affect safety factors, and simulation provides management tools to address organizational, technical, and human factors.

2.7 Conclusion

To conclude this chapter, it is important to mention that decision-making in complex systems is an arduous task for those who base themselves solely on mental models. The frameworks to create the models are well-grounded in the literature and the system dynamics tools are consolidated to the point of generating useful information, both quantitative and qualitative. In this context, real-world feedbacks can be visualized in short- and long-term charts, which makes decision-making more assertive regarding the expected results.

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CHAPTER 3 | Physical and Mental Workload Assessment in Human-Robot Collaboration Workplaces – a Review

Abstract. HRC systems are often chosen to improve ergonomics in manual tasks. There are many metrics available to quantify the ergonomic benefits when implementing an HRC. It is important to understand which metrics (ergonomic methods, tests, questionnaires) are being used by researchers in terms of physical and mental workload assessment. Therefore, the aim of this work was to review the literature on the subject and to provide key information for further investigations. A literature review was carried out in four databases and the findings were categorized into theoretical surveys and empirical studies from the last five years. Results show the emerging research fields that were identified and analyzed. The metrics used to assess physical and mental workloads were discussed and a new meaning of these results is proposed in the sense of using a global ergonomic risk assessment as input in simulation models.

3.1 Introduction

HRC increases in importance due to new developments in industry 4.0. An effective collaboration between humans and robots means a combination of their skills: precision, speed, and fatigue-free operation of the robot; cognitive and sensorimotor of the human. The relevant human factors in the context of the HRC system were compiled by Rücker, Hornfeck, & Paetzold (2019).

Manufacturing industries sometimes do not successfully implement HRC systems due to a lack of understanding of human and social related issues (Charalambous et al., 2016). In general, greater collaboration induces less physical workload on workers, as some tasks are allocated to the robot. On the other hand, greater collaboration could increase mental strain, although it depends on the level of human trust, robustness, and reliance on the HRC system (Vazquez & Jabi, 2019). Physical fatigue is a transient inability of muscles to maintain a load, a decrease in the maximal force that the involved muscles can produce and develops due to sustained physical activity (Enoka & Duchateau, 2008). Mental fatigue is a transient decrease in maximal cognitive performance resulting from prolonged periods of cognitive activity (Marcora, Staiano, & Manning, 2009).

In Gualtieri, Rauch, & Vidoni (2021), it was reviewed the literature regarding safety and ergonomics in HRC. The present work focuses on revising only ergonomic assessment studies in HRC systems.

3.2 Method

The current state of the art regarding risk assessment in HRC was organized by synthesizing the empirical studies where physical and mental workloads were considered. It was applied the Systematic Search Flow (SSF) method (Ferenhof & Fernandes, 2016), because it is based on a systematic and replicable approach. The SSF method includes a research protocol followed by analysis of all the relevant studies, synthesis, and write. Therefore, it is characterized by a scientific process that aims to avoid researcher bias.

It was used four of the main scientific databases: Scopus, Web of Science, Science Direct, and PubMed. The search contained the following terms and variations: (ergonomics OR 'human factors') AND ('human-robot collaboration' OR HRC OR cobot) AND (assembly OR industry OR manufacture OR production). In order to be included in this review, it was mandatory that the documents were available in english with full-text access either in the scientific databases, in Google Scholar® or Research Gate®.

The databases were accessed on April, 2021 and the query was limited to search in the titles, keywords, and abstracts from the last 5 years. In total 415 documents were downloaded and exported to the Mendeley bibliographic referencing software. After excluding the duplicates, the portfolio resulted in 320 full-text documents assessed for eligibility. The inclusion criteria is that the article reports a case study where ergonomic aspects were taken into account in an HRC system. The papers that were considered not relevant or out of scope were excluded by the authors and 67 were considered for a preliminary overview of ergonomic metrics in HRC systems. Finally, 23 papers were included in the portfolio analysis.

3.3 Results and Discussion

Ergonomic methods for physical assessment can be divided in three categories: self-reports, observational methods, and direct methods. Advantages and limitations are described as follows: self-reports can be used to collect data on exposure to physical factors using questionnaires, however results are limited by worker's perceptions and answers; observational methods are widely used to evaluate postures and movements of the workers, however it requires an ergonomic expert to assess workplace hazard through observation; and direct measurement provides data using sensors (e.g., cameras, wearables) during task execution, however, it is more complex to apply as it often requires to place the devices on the worker's body (David, 2005). The selection of ergonomic methods is based on their characteristics, the characteristics of the task and the nature of the problem (Berlin & Adams, 2017). In this literature review, it was pursuit papers that applied either technologies for physical ergonomic measurement (Table 3-1) or NASA-TLX questionnaire for measuring mental workload (Table 3-2). Physical ergonomics is discussed in terms of communication between human and robot as human can wear sensors for motion tracking or the robot is equipped with sensor cameras to capture human intentions. The cognitive ergonomics is subjective, in which mental workload is compared for different groups of workers (age, gender) or different robot configurations (level of collaboration, robot speed).

3.3.1 Physical assessment

Observational methods are well-established tools, however sensor-based direct measurements are more precise and can be real time updated. Some softwares embed ergonomic modules based on standard ergonomic assessment worksheets such as RULA, REBA and EAWS. Table 3-1 presents the studies that approached technology to qualify and quantify ergonomic risks in HRC workplaces.

Table 3-1. Studies that used technologies for ergonomic measurement in HRC.

Authors	Year	Measurement technique	Complement
Kim et al.	2021	Xsens (REBA) / EMG	Safety
Ferraguti et al.	2020	ASUS Xtion (RULA)	Questionnaire (usefulness)
Paletta et al.	2020	EDA (stress)	
El Makrini et al.	2019	Skeleton joint angles (REBA)	Assembly time
Kim et al.	2019	Stereo-vision camera	Productivity
Peternel et al.	2019	Camera with machine learning (fatigue)	
Parsa et al.	2019	Camera with deep learning (REBA)	
Lorenzini et al.	2019	Xsens	
Kim et al.	2018	Xsens / EMG	
Nguyen et al.	2016	Microsoft Kinetics (EAWS)	
Thomas et al.	2016	Famos Robotic (DHM)	REBA
Pini et al.	2016	Delmia V5 (DHM)	Fatigue (RULA / EE)

REBA (Rapid Entire Body Assessment); RULA (Rapid Upper Limb Assessment); EAWS (Ergonomic Assessment Worksheet); EE (Energy Expenditure); EMG (Electromyography); EDA (Electrodermal Activity); DHM (Digital Human Modeling). Wearable motion tracking based on inertial sensors: Xsens; Microsoft Kinect; ASUS Xtion.

3.3.1.1 Wearable

Human motion can be captured by wearable sensors to communicate gestures to the robot. Kim et al. (2021) proposed a method to minimize overloading joint torque while considering manipulability. The workers were equipped with Xsens and EMG sensors for motion track and muscle activity. A comparison between six standard and one optimized task configurations was made. Results showed that the optimized configuration presented significantly higher manipulability capacity of the arm, which could positively affect the task production, although the overall joint torque is lower in three of the predefined configurations. Ferraguti et al. (2020) proposes an architecture for an optimal posture, in which the robot is programmed to always offer the human a comfortable position corresponding to a minimum RULA level. The tracking of the human body is performed with ASUS Xtion and the results showed that the strategy optimizes ergonomic posture when executing tasks. Paletta, Pszeida, Nauschnegg, Haspl, & Marton (2020) investigated how cognitive stress affects eye-hand coordination in multi-tasking processes. Measures were made by EDA biosensors (arousal) and eye tracking glasses. Results demonstrated high correlation between stress and error. Lorenzini et al. (2019) proposed a fatigue model to estimate the risk in repetitive light-weight tasks. The model takes into account the variability of the load and the individual perception of the fatigue. The whole-body tracking motion sensors (Xsens) process data in real-time to avoid fatigue accumulation by optimizing HRC. Kim, Lee, Peternel, Tsagarakis, & Ajoudani (2018) proposed a real-time technique for reducing joint torque in HRC, in which overload alerts the human about consequent injuries. Measurement of the whole-body human motion was made using Xsens. EMG was also used to confirm the reduction of muscular activity. The optimized scenario resulted in less 40-50% joint torques in shoulder and elbow.

3.3.1.2 Image-based

Sensor cameras are often used to inform the robot about human intentions. El Makrini et al. (2019) describe a framework for task allocation in HRC gearbox assembly considering the human body posture. The human tracking system uses a depth camera-based that assesses the skeleton joint angles provided by the human tracking system. The data are used to calculate REBA manually. It has been concluded that setting the workload limit at a desired level leads to a decrease of 14% in the overall assembly time. Kim et al. (2019) proposes a real-time adaptation in HRC. The task was optimized to human intentions and captured movements by a stereo-vision camera. The results showed a lower overloading effect in all joints compared to the initial configurations, contributing to better ergonomics. Peternel, Fang, Tsagarakis, & Ajoudani (2019) use a camera with machine learning technique and a musculoskeletal model to estimate online the human muscle fatigue. Thus, the robot can switch configuration of task production to facilitate safer and more ergonomic work. Parsa et al. (2019) present a deep learning system using camera videos to segment human actions. The real-time ergonomic risk is computed based on the skeletal model extracted from the videos and calculates the REBA scores assigned for each action. Nguyen, Bloch, & Krüger (2016) use the Microsoft Kinect sensor embedded with EAWS to assess the worker's posture and optimize the pose of the work piece to be processed. When the risk exceeds an acceptable score, the system alerts the worker and suggests a more natural posture. Results show that all postures were critical and after optimization most of the postures were acceptable.

3.3.1.3 Digital Human Modeling

DHM is a human simulation solution to design and evaluate workstations, worker safety, and system performance. It can embed ergonomic modules based on ergonomic methods such as RULA, REBA, EAWS to identify critical postures and to plan the assistance of a robot. Thomas et al. (2016) shows a concept to implement HRC based on the task specific movements of the employee that is simulated using DHM in the virtual environment Famos Robotic. HRC system is simulated considering an employee's physical constraints combined with REBA to assess postures. Pini, Ansaloni, & Leali (2016) is based on a DHM and simulation of the human body at the platform Delmia V5 to propose a modified model that integrates RULA and Energy Expenditure as ergonomic metrics to calculate fatigue. Results show that implementing HRC unburdens the human operator and increases the overall ergonomic level as the fatigue index drastically dropped.
In summary, different technologies are being applied to assess physical risk in HRC and it is often seen that traditional ergonomic methods are embedded in these software.

3.3.2 Cognitive assessment

NASA-TLX is a subjective, multidimensional assessment tool that rates perceived workload in order to assess a task (NASA, 1986). NASA-TLX is divided into six items: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort and Frustration. A weighting scheme is used to compute an overall workload score. NASA-RTLX is referred when weighting the items was not considered. Table 3-2 presents the case studies where NASA-TLX and NASA-RTLX were used to assess cognitive ergonomics in HRC systems. The column labeled as "complement" presents other relevant factors taken into account.

Table 3-2. Studies that used NASA-TLX in HRC.

Authors	Year	Cognitive	Complement
Rossato et al.	2021	NASA-TLX	UX / SUS / TAM
Hopko et al.	2021	NASA-TLX	SART
Gervasi et al.	2020	NASA-TLX	EAWS / SUS (trust)
Pantano et al.	2020	NASA-TLX	Safety
Sadrfaridpour and Wang	2018	NASA-TLX	Cycle time Questionnaire (trust, satisfaction)
Materna et al.	2018	NASA-TLX	SUS (mental demand)
Rahman et al.	2018	NASA-RTLX	Productivity, trust, quality
Koppenborg et al.	2017	NASA-TLX	Cycle time / Error rates Questionnaires (risk, anxiety)
Ustunel and Gunduz	2017	NASA-RTLX	
Sadrfaridpour et al.	2016	NASA-TLX	Questionnaire (trust)
Sadrfaridpour et al.	2016	NASA-TLX	Performance (trust scale)

UX (User Experience); SUS (System Usability Scale); TAM (Technology Acceptance);
SART (Situation Awareness Rating Technique).

The following discussion is divided in studies that used the NASA-TLX to make mental workload comparisons: between groups (i.e., by gender; by age); and between different HRC configurations (i.e., with varying levels of automation).

3.3.2.1 Comparison between groups

Hopko, Khurana, Mehta, & Pagilla (2021) studied the interplay of operators' gender, their cognitive fatigue states, and varying levels of automation on HRC. In the analyzed situation, women perceived higher mental demand when fatigued than males. With increased assistance of the robot, women felt performed better while man did not. Ustunel & Gunduz (2017) performed an experiment about the effects of workplace design considering both extended cognition and gender differences in cognitive load. For the gender differences, NASA-RTLX were used. Results showed no significant differences between male and female groups for each NASA-TLX item. Rossato et al. (2021) investigated the subjective experience of younger and senior workers interacting with an HRC. They compared group (senior vs. adult operators) and mode (manual vs. tablet) effects on acceptance, UX, usability, and task load related to HRC. For the task load assessment, the NASA-TLX was employed. They find out that higher physical demand, higher temporal pressure, and higher frustration were reported by senior workers in the manual mode, while adult workers reported a higher perceived performance. Gervasi, Mastrogiacomo, & Franceschini (2020) proposed a framework to evaluate and compare HRC configurations according to eight latent dimensions: autonomy, information exchange, adaptivity and training, team organization, task, human factors, ethics, and cyber security. Within the human factors dimension, the NASA-TLX was used to assess the workload. They simulated an assembly task in the laboratory, and although the study does not present results for each of the six items, the global workload resulted 32.5/100.

3.3.2.2 Comparison between HRC configurations

Interaction in HRC configurations was compared in Pantano, Regulin, Lutz, & Lee (2020): normal interaction, provided by the robot through a smartpad, interface with gaze, and touch inputs. The overall workload calculated through NASA-TLX were 16.15 (Normal), 13.03 (Gaze) and 9.21 (Touch). Materna, Kapinus, Beran, Smrz, & Zemcik (2018) proposed an interactive system to reduce the mental demands and attention switching by centering all interactive elements in the shared workspace. In order to evaluate the proposed approach and to discover the main usability issues of the early prototype, they carried out a user experience testing using NASA-TLX, which resulted in a global workload of 33.3. Human's trust in robot and robot's trust in human are considered in Rahman & Wang (2018). Real-time trust measurement of computational models was developed to test three schemes (no trust, one-way trust, and two-way trust) regarding productivity, quality, team fluency, situation awareness, and the six dimensions of the NASA-TLX. Results were better when human and robot trust each other.

Robot speed conditions were carried out for different HRC. As robots execute movements at high levels of automation, they adapt their speed and movement path to situational demands. Koppenborg, Nickel, Naber, Lungfiel, & Huelke (2017) experimentally investigated the effects of movement speed and path predictability of an HRC on the human operator. They used NASA-TLX to compare low-speed condition (40.7) to high-speed condition (44.7). Sadrfaridpour, Saeidi, Burke, et al. (2016), Sadrfaridpour et al. (2016), and Sadrfaridpour & Wang (2018) studied HRC considering robot performance, tying robot speed to human mental workload considering three conditions. In the manual condition, the participant can adjust the robot path velocity during the entire experiment. In the pHRI-based approach, the robot motion is synchronized with that of the human. In the integrated scenario, trust and human performance are included for better joint human-robot system performance. The workload was assessed by NASA-TLX, and the overall workload for each scheme were 30.9 (manual), 25.7 (pHRI), and 19.1 (integrated).

In summary, unlike physical assessment, cognitive workload has a subjective characteristic, and it is more often assessed through NASA-TLX in HRC. NASA-RTLX that was proposed in Rahman & Wang (2018) and Ustunel & Gunduz (2017) indicates that a specific questionnaire for cognitive workload could be developed to be a new standard in HRC. There are also studies proposing a computational model for real-time trust measurement (Rahman & Wang, 2018) and an electrodermal sensor for stress measurement (Paletta et al., 2020).

3.4 Conclusion

According to the aim of this chapter, the literature review provided key information for further investigations on the topic of physical and cognitive risk assessment in HRC systems. The physical risk assessment was discussed in terms of communication between human and robot (wearables, image-based, and digital human modeling). Mental workload was analyzed through empirical studies that applied the NASA-TLX questionnaire comparing different groups of workers (age, gender), or different robot configurations (level of collaboration, robot speed). Finally, these results are presented as input for simulation models in the next chapters to predict the system's behavior.

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CHAPTER 4 | Human factors effects on a Human-Robot Collaboration system: a modelling approach

Abstract. This chapter introduces a system dynamics-based model for designing feedback mechanisms related to the physical and mental workload in HRC systems. As a dynamic and non-linear system, HRC workplaces challenge ergonomic operations in the medium and long terms, and it is crucial to understand the whole system in order to increase reliability in decision-making about ergonomic interventions. The aim of this chapter is to define which variables are to be considered and how they interact to predict the behavior of the HRC system over time. The method applied in the work follows four phases: literature review to systematic search for case studies and theoretical literature embracing the objectives of this work; summary of factors in HRC systems and their relationships obtained through the review of previous studies; definition of variables for the model gathered in a way they became the variables to be modeled; design of the Causal Loop Diagram (CLD) as a qualitative model developed from the variables, which formalizes and delimits the context to be analyzed. This chapter proposes the conceptual definition by considering both physical and mental overload as a cause of WMSD and influence on productivity. The work shows both subsystems, how they are connected, and reinforce the importance of looking at ergonomic problems with a systemic approach. Modeling the whole system is key to solve ergonomic problems in industry. The qualitative model CLD provided through the literature review is useful in understanding HRC systems.

4.1 Introduction

The development of HRC workstations has been a need for the industry. Despite their rise in popularity, integrating a collaborative robot into a work process poses many challenges and variables. Production time, quality, efficiency, and minimization of safety risks are often used as criteria for assessing the performance of HRC. Recent works have also considered ergonomic consequences of task allocation and schedule in order to maximize global reward while minimizing cost, i.e., by considering both production time and physical stress when generating human-robot task plans (Pearce et al., 2018). However, prior research on HRC workstations does not offer a flexible and operational solution for quantifying the variables involved or exploring their tradeoffs and behavior along a time horizon. A human-machine system exists in an environment within boundaries. It is characterized by its structure, and elements that interact to achieve the goals of a system (Salvendy, 2012). For a successful implementation of a HRC system, ergonomics needs to be considered (Charalambous, Fletcher, & Webb, 2015), with the three dimensions of ergonomics - physical, cognitive and organizational (Ender et al., 2019). By not considering ergonomics, the HRC system may present undesired effects, such as fatigue, monotony, and performance decrements (Green et al., 2008). Regarding the risk factors to develop WMSD, EU-OSHA (2020) states that they can be physical, biomechanical, individual, organizational, psychosocial, and they often work in combination. As a dynamic and non-linear system, HRC workplaces challenges ergonomic operations in the medium and long terms resulting in difficulties to predict their future behavior (Saurin & Gonzalez, 2013), particularly when involving ergonomics (Mattos et al., 2019). Therefore, the aim of this chapter is to define which variables are to be considered and how they interact to predict the behavior of the HRC system over time.

4.2 Theoretical Background

4.2.1 Ergonomic domains

Ergonomics can be divided by areas of specialization in three main domains: physical, cognitive, and organizational (IEA, 2020; Salvendy, 2012):

- Physical ergonomics focuses on human anatomical, anthropometric, physiological, and biomechanical characteristics as they relate to physical activity. Examples of relevant topics include working postures, materials handling, repetitive movements, work related musculoskeletal disorders, workplace layout, safety, and health. These factors applied in the workplace are concerned with improving the work tools as well as the environmental and workstation conditions.
- Cognitive ergonomics covers mental processes, such as perception, memory, reasoning, and motor response, as they affect interactions among humans and other elements of a system. Examples of relevant topics include mental workload, decision-making, skilled performance, human-computer interaction, human reliability, work stress and training as these may relate to human-system design. These factors focus on explaining the cognitive aspects of the relationship between human action and the physical and material elements of the environment.
- Organizational ergonomics is concerned with the optimization of sociotechnical systems, including their organizational structures, policies, and processes. Examples of relevant topics

include communication, crew resource management, work design, design of working times, teamwork, participatory design, community ergonomics, cooperative work, new work paradigms, virtual organizations, telework, and quality management.

4.2.2 Risk assessment

These factors interact directly on issues related to human behavior and labor relations. Depending on the LoC to perform the same task, it is expected different physical and mental workload over the human being. In general, physical workload decreases with collaboration due to less effort, although it depends very much on which tasks are allocated to the robot. As stated by Sluiter, Croon, Meijman, & Frings-Dresen (2003), specific risk factors to WMSD include analysis of awkward postures (e.g., limbs, joints and back out from the neutral position), static load sustained for a prolonged time, and lack of sufficient rest. On the other hand, mental strain increases with collaboration due to complexity, although it depends which safety functions are programmed, if workers trust the robot.

There are several ergonomic methods for the risk assessment of WMSD (David, 2005) and the selection is based on their characteristics, the task under analysis and the nature of the problem (Salvendy, 2012):

- Self-reports, in which interviews or questionnaires are applied to collect data from worker's physical and psychological perceptions. Self-report methods (e.g., NQM and NASA-TLX) are easier to apply with large groups at low cost, however, there are major problems when comparing data in workers with and without WMSD due to their perception in terms of intensity, frequency and duration (Wiktorin, Karlqvist, & Winkel, 1993).
- Observational methods (e.g., RULA, REBA, OCRA, NIOSH, EAWS, KIM-MHO, and EWA) consist of visual analysis or video recordings of the workplace risk exposure by observation of predefined ergonomic risks, like work postures, gestures or movements. It allows experienced ergonomists to easily assess the risk factors for the occurrence of WMSD without any special equipment. To choose between different options, it depends on which tasks are under observation as it may be interesting to assess general workload, workload on upper limbs or manual material handling (Takala et al., 2010).
- Direct or instrumented-based methods use devices placed on the worker's body for measuring change in the skin's electricity or posture strain assessment (e.g., EDA and EMG) and wearable

technologies for measuring motion capture and grip pressure during work (e.g., Xsens® and CyberGlove®).

According to EU-OSHA (2020), the risk factors to develop WMSD can be physical, biomechanical, organizational, psychosocial, individual, and they often work in combination. Moreover, ergonomics should involve a systemic view, in which analysis and interventions consider the understandings of the whole system (Karsh, Waterson, & Holden, 2014). HRC can reduce risk factors, while keeping workers in control of the task execution (Krüger, Lien, & Verl, 2009; Schmidtler, Knott, Hölzel, & Bengler, 2015). As stated by Green et al. (2008), not reasoning ergonomics in complex systems with HRC may present undesired effects.

4.3 Method

The method applied in this work follows four phases represented in Figure 4-1.

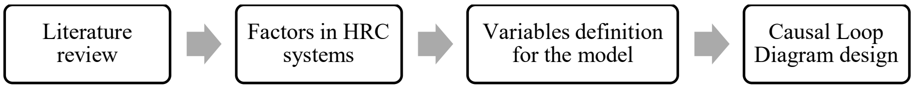

Figure 4-1. Method used to develop the causal loop diagram.

Phase 1 (Literature review) - a review following the Systematic Search Flow method (Ferenhof & Fernandes, 2016) has been established as a research plan for three systematic searches embracing the objectives of this work. The databases were searched on August, 2020 from the last 5 years, with the following queries: ("ergonomic*" OR "human factor*") AND ("dynamic*system*" OR "system*dynamic*"); ("ergonomic*" OR "human factor*") AND ("human*robot" OR HRC); ("dynamic*system*" OR "system*dynamic*") AND ("human*robot" OR HRC). The process is shown in Table 4-1.

Table 4-1. Articles in the portfolio.

Database	Number of articles
Scopus	354
Web of Knowledge	199
TOTAL	553
After excluding duplicates	420
After excluding out of scope articles	16

Phase 2 (Factors in HRC systems) - The contributing factors and their relationships were summarized in the column labeled “comments” in Table 4-2.

Phase 3 (Variables’ definition of the model) - The factors gathered were grouped in a way they became the variables to be modeled. Some factors are presented in more than one ergonomic domain, which means they influence the system in different ways.

Phase 4 (CLD design) - The construction of the qualitative model was developed from the variables found in Phase 3. The conceptual model CLD formalizes and delimits the context to be analyzed. This diagram outlines the relationships among the variables of the system using a system of lines and arrows, where the arrows indicate the direction of causality.

4.4 Results

4.4.1 Ergonomic factors in HRC

Table 4-2, Table 4-3, * Factors that are not considered in the model due to irrelevance in the present study.

Table 4-4, and * Factors that are not considered in the model due to irrelevance in the present study.

Table 4-4 show the results of the analysis of the surveyed literature regarding ergonomics factors that influence HRC. Although different terms have been used to label factors to consider in HRC system, for the model of this work they have been grouped into a representative variable. In the comments' column, the words in italics inside parentheses are the different expressions found in the literature for a given factor. Although different terms were used, they were grouped into a single term represented by the first column. The criteria for inclusion in the CLD was decided by the author as the model has to be as simple as possible, and some variables brings too much uncertainty to be simulated afterwards.

Table 4-2. List of physical variables.

Physical		
Repetitive movements	(Abaeian et al., 2017, 2016; Farid & Neumann, 2019; Lorenzini et al., 2019; Mattos et al., 2019; Pini, Ansaloni, & Leali, 2016; Rücker et al., 2019)	Physical overload caused by repetition (stereotyped movements, fatigue).
Cycle time	(Farid & Neumann, 2019; Mattos et al., 2019)	Time between the beginning and the end of a process (cycle time) or the speed a process has to occur depending on the demand (takt time).
Recovering time	(Farid & Neumann, 2019; Mattos et al., 2019)	Time to rest and to reduce physical overload and is related to the shift length. Recently considered in models as a way to reduce physiological factors.

*Health and safety climate, circadian rhythm	(Abaeian et al., 2017; Fruggiero et al., 2018; Rücker et al., 2019)	Very peculiar characteristic of the worker that can vary a lot and are difficult to measure, but were considered to influence a socio-technical system.

* Factors that are not considered in the model due to irrelevance in the present study.

Table 4-3. List of cognitive variables.

Cognitive		
Performance pressure	(Abaeian et al., 2017, 2016; di Nardo et al., 2015; Jafari et al., 2019; Neubauer et al., 2015; Rücker et al., 2019)	Cognitive factors related to performance pressure (strain, stress, fatigue).
Task complexity	(Fruggiero et al., 2018; Pini et al., 2016)	Cognition or mental complexity of the task that result in mental workload.
Training	(Abaeian et al., 2017; di Nardo et al., 2015; Fruggiero et al., 2018; Rücker et al., 2019)	Importance of training in the resulting mental workload (knowledge, skill, competence, awareness, safety climate, experience, expertise).
Trust in the Robot	(Charalambous et al., 2015; Koppenborg, Nickel, Naber, Lungfiel, & Huelke, 2017)	Mental impact of the robot on the individual (reliability, safe co-operation, motion speed, predictability, exterior design, appearance)
*Self-recompensing	(Abaeian et al., 2017; di Nardo et al., 2015; Fruggiero et al., 2018)	Mental comfort for fulfilling the work (motivation, satisfaction, a feeling of competence)
*Self-punishment	(di Nardo et al., 2015; Rücker et al., 2019)	Mental discomfort for not fulfilling the work (human error).
*Absenteeism	(Neubauer et al., 2015)	Mental workload for doing work of an absent worker.

* Factors that are not considered in the model due to irrelevance in the present study.

Table 4-4. List of organizational variables.

Organizational		
Workplace environment	(di Nardo et al., 2015; Fruggiero et al., 2018; Neubauer et al., 2015; Pini et al., 2016; Ranz et al., 2018; Rücker et al., 2019)	Organizational characteristics of the workplace (layout, risk level, field of view) and environment factors (noise, illumination, temperature) that impose itself over the system.
*Participatory implementation	(Charalambous et al., 2015; Chavalitsakulchai, Ohkubo, & Shahnavaz, 1994; Neubauer et al., 2015; Rücker et al., 2019)	Ergonomic interventions are more efficient when workers take part in decisions and ideas (participatory in designing and implementing changes in the workplace).
*Top management support	(Abaeian et al., 2017; Charalambous et al., 2015; Chavalitsakulchai et al., 1994; Rücker et al., 2019)	Efficacy of a manager (communication, supervisor's effectiveness).
*Design of working times	(Abaeian et al., 2017; Farid & Neumann, 2019; Fruggiero et al., 2018; Mattos et al., 2019; Neubauer et al., 2015; Rücker et al., 2019)	To plan the overall production (shift length, working hours, cycle time, takt time, recovering).
*Empowerment of the workforce	(Abaeian et al., 2017, 2016; Challenger et al., 2012; Charalambous et al., 2015)	To keep the worker in a position to make decisions, especially in the presence of a robot (workers' control over the work).
*Team work	(Abaeian et al., 2017; Neubauer et al., 2015; Rücker et al., 2019)	Friendly team (team work, co-worker's support)
*Procedures	(di Nardo et al., 2015; Rücker et al., 2019)	Organizational importance of procedures (safe methods, procedures).
Task complexity	(Abaeian et al., 2016; Rücker et al., 2019)	Organizational impact of the task complexity (task complexity, difficulty, multi-tasking requirement).
Recovering time	(Abaeian et al., 2016; Fruggiero et al., 2018)	Organizational caution over worker's recovering (recovery break).
Absenteeism	(Farid & Neumann, 2019; Mattos et al., 2019)	Organizational problems caused by the absence (absenteeism)

Training	(Charalambous et al., 2015; Mattos et al., 2019)	Organizational gains by knowledge of the workforce (training workforce, task knowledge).

* Factors that are not considered in the model due to irrelevance in the present study.

Table 4-5. List of middle zone between physical and cognitive variables.

Physical and Cognitive		
Workplace environment	(Abaeian et al., 2016; di Nardo et al., 2015; Fruggiero, Fera, Iannone, & Lambiase, 2018; Pini et al., 2016; Rücker et al., 2019)	Physical characteristics of the workplace that impose itself over the worker (light, temperature, noise, vibration) or physical characteristics of the workplace that impose to the worker the way to behave (layout, working postures).
	(di Nardo et al., 2015; Fruggiero et al., 2018; Neubauer, Krenn, & Majoe, 2015; Pini et al., 2016; Ranz et al., 2018; Rücker et al., 2019)	Mental characteristics of the workplace that impose itself over the worker (layout, field of view) or environmental factors (noise, illumination, temperature).
Work-related Musculoskeletal Disorder - WMSD	(Abaeian et al., 2017; Farid & Neumann, 2019; Mattos et al., 2019; Pini et al., 2016; Rücker et al., 2019)	WMSD caused by physical and mental overload (biomechanical stress, illness).
Individual characteristics	(di Nardo et al., 2015; Farid & Neumann, 2019; Fruggiero et al., 2018; Pini et al., 2016; Rücker et al., 2019)	Physical characteristics of an individual (anthropometric measurements, height, weight, sex, age) or measures over the effort when working (magnitude of the load, contact forces, body segments position).
	(Fruggiero et al., 2018; Jafari et al., 2019; Rücker et al., 2019)	Mental characteristics of an individual (self-confidence, personality, attentional capacity, and attitude) in the presence of a robot (comfort towards robots).
Level of Collaboration (LoC)	(di Nardo et al., 2015; Pini et al., 2016; Ranz et al., 2018; Rücker et al., 2019)	Effects of the robot collaboration on physical workload (level of collaboration, predictability, and interface).

4.4.2 Design of the Causal Loop Diagram

The relations between variables followed the connections noticed in the literature as well as logic and the author's experience when needed. The nomenclature is slightly different in the next chapters as the CLD evolves. To facilitate the understanding of the CLD, it was divided into two subsystems: physical workload and mental workload. These cycles are respectively identified by the green and red boundaries in Figure 4-2, which are individually discussed in section 5.

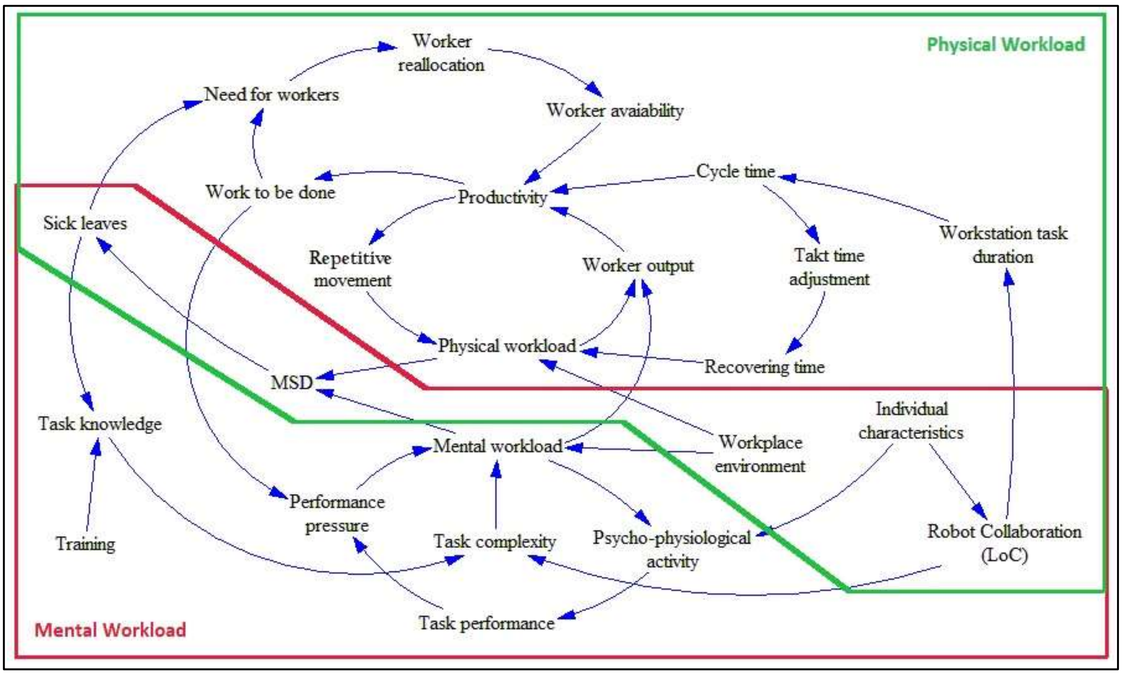

Figure 4-2. Causal Loop Diagram in an HRC system.

4.5 Discussion

In order to discuss the dynamic of this HRC system, it is divided in Subsystem Physical Workload and Subsystem Mental Workload. When teaming a human with a robot, workers' physical variables to be taken into account and used to inform the robot are anthropometric measures, postures, and ranges (Abaeian et al., 2016; Fruggiero et al., 2018; Pini, Ansaloni, & Leali, 2016; Rücker et al., 2019), while cognitive variables are attention capacity, reliability, personality traits, and attitude towards robots (Fruggiero et al., 2018; Jafari et al., 2019; Rücker et al., 2019). There are also variables in the middle zone that are either cause or effect for both physical and metal workloads. Therefore, this work reinforces the importance of looking at ergonomic problems with a systemic approach. Both physical and mental workloads are to be considered in an HRC system.

4.5.1 Subsystem Physical Workload

Physical overload results in fatigue and WMSD, leading to sick leaves and impacting production (Abaeian et al., 2017, 2016; Farid & Neumann, 2019; Lorenzini et al., 2019; Mattos et al., 2019; Pini et al., 2016; Rücker et al., 2019). In this subsystem the physical workload is indirectly affected by the productivity through repetitive movements, as well as by the cycle time taken into account the recovering time. This is less obvious, but still very intuitive, and also confirmed by literature. WMSD evolve to sick leaves and ultimately affects productivity, which affects physical overload.

LoC influences the cycle time, which very much impact productivity and, finally, affects physical overload.

4.5.2 Subsystem Mental Workload

Mental workload is a response that depends on physiological active mechanisms, where the worker output can be expressed in physiological feedbacks (Ryu & Myung, 2005; Mehler, Reimer, Coughlin, & Dusek, 2009). In this subsystem mental workload is directly influenced by workplace environment and task complexity. It is also indirectly affected by productivity as it increases performance pressure. When mental workload exceeds workers' mental limits it is called mental overload, which is in a cycle that increases performance pressure, as it burns psycho-physiological activity. WMSD is a direct consequence of mental overload. As already discussed, sick leaves affect productivity, but also task knowledge, which increases task complexity.

4.6 Conclusion

This chapter proposes a model to enable the design of HRC workstation considering it as a complex system and providing insights using a qualitative model. Modeling the whole system where ergonomics is involved is key to solve ergonomic problems in industry. The represented HRC system includes the three main aspects of ergonomics: physical, mental, and organizational. This qualitative model is useful for computer simulations regarding workstations with HRC. Next chapters develop the following phases of the system dynamic analysis, namely, the structural description and the quantification and prospection.

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CHAPTER 5 | A Computational Assessment of Ergonomics in an Industrial Human-Robot Collaboration Workplace Using System Dynamics

Abstract. An automotive company in Portugal has a high rate of sick leave due to occupational diseases where it is planned the insertion of an industrial HRC system to assist workers' activities. As this system can result in physical and mental overload, depending on the different LoC, the aim of this chapter is to predict what would be the best working condition between worker and robot. This descriptive research establishes a quantitative approach, since it prospects scenarios generated by computer simulation. It explores the outputs of sick leave rate by inserting an industrial HRC in the production line. The main results consist of the scenarios that graphically describe the evolution of the indicators over time. It was concluded that counterintuitive effects can occur in these systems, and a computational simulation is useful to predict working condition scenarios when deciding which human-robot configuration fits better.

5.1 Introduction

An automotive company in Portugal plans to insert a robotic system to collaborate with a worker hoping to reduce physical overload. It is expected that an effective collaboration between humans and robots would result in combining their skills: precision, speed and fatigue-free operation of the robot with human sensory perception, and cognition.

It has been described in Mattos, Ariente Neto, Merino, & Forcellini (2019), that managers tried to increase production expecting certain productivity, it caused physical overload on workers, consequent sick leave, knowledge losses, leading to productivity below expected values, and finally resulting in counter intuitive effects.

Therefore, this chapter establishes a preliminary approach to the problem exploring the basic reflexes of the insertion of an industrial HRC system. Considering the nonlinear characteristic of the system's behavior, this chapter introduces a model based on System Dynamics (SD) representing the feedback mechanisms related to physical and mental overload, as well as the LoC of the robotic system with a focus on task accomplishment.

The computational model simulates scenarios that graphically describe the behavior of the main indicators. The aim is to draw guidelines that evolve the model into a structure to apply in a practical analysis of a production line.

5.2 Theoretical Background

5.2.1 Ergonomics and Robotics

Automation and robotics replace humans in difficult manufacturing process tasks, however, it is important to take into account ergonomics, as it is often a barrier in organizations when introducing a new technology (Charalambous, Fletcher, & Webb, 2015). Despite ergonomic improvements in workplaces, workers are exposed to physical and mental workloads at assembly processes in the industry, which leads to absenteeism due to WMSD (Bokhorst, Nomden, & Slomp, 2008; EU-OSHA, 2020). As WMSD develops over time, workers begin to fatigue when exposed to WMSD risk factors. Manual handling workstations often lead to awkward postures, repetitive movements and forceful exertions, which are the main factors for WMSD (Naik & Khan, 2020). When biomechanical demands repeatedly exceed workers' physical capacity and fatigue exceeds the body's recovery system, it develops a musculoskeletal imbalance from which a WMSD occurs (Mukhtad, Aminese, Mansor, Salam, & Elmesmary, 2018; Punnett & Wegman, 2004).

Robots may have perception of physical structures, operate physical parts autonomously, sense and manipulate their environment, and behave thanks to machine learning algorithms. These machines have been very useful in replacing humans specially by performing repetitive and dangerous tasks. Also, there is no limit for strength or an environment where robots can replace humans. In HRC system, the ultimate goal is to include a robot capable of communicating and coordinating with a human operator effectively (Sharma, 2006) in order to improve productivity and ergonomics.

5.2.2 Levels of Collaboration

The type of interaction refers to the common goals of human and robot during a task as well as their temporal and spatial relation. The concept LoC is assigned to the interaction human-robot. Higher LoC means that the robot is more capable to perform tasks as a teammate.

The conventional way to deal with industrial robots means physical isolation (Level 0). A coexistent work means no fence to separate physically robots and humans, although they work separately and independently (Level 1). In synchronization, robots and human share a common workspace, but not at the same time (Level 2). In cooperation, human and robot operate the workstation simultaneously, but working on different tasks or at least not manipulating the same object at the same time (Level 3). The last level of collaboration means sharing the workstation with a common goal and simultaneously manipulation of the same object (Level 4) (Bauer, Bender, Braun, Rally,

& Sholtz, 2016; Bdiwi, Pfeifer, & Sterzing, 2017; Ranz et al., 2018). Recently, a new proposal on this topic was made considering the capabilities of a cobot, which includes: safety (from Level 1 stopping the cobot in proximity of the operator to higher levels with more challenging control mechanisms); input (from Level 1 using only force and proximity sensors to higher levels with the addition on cameras, various sensors, and internet of things); mobility (from Level 1 stationary basis to higher levels with wheeled platform, laser sensors, autonomous unit with increased flexibility); actuation (from Level 1 with self-set-up after collision and repeatability to higher levels of competence being capable of reassessing its new location, dynamic corrections of the trajectory to avoid collision and actively plan and dynamically adjust the trajectory); status tracking (from Level 1 fundamental kinematic profile tracking to higher levels with addition of task-related status tracking); intelligence (from lower levels to higher levels of awareness in terms of being capable of interaction with the operator, awareness of its environment and the operator intention to improve fluency); interaction (from Level 1 in which the cobot should communicate its status and real-time alarms to higher levels of communication related to gesture recognition, speech recognition and artificial intelligence ability to be invoked by the operator); and human support (from Level 1 by performing repetitive and dangerous tasks to higher levels performing uncomfortable postures, in nasty environments, identifying dangers and issue safety warnings, bringing tools or work pieces next to the operator and take them away, up to manipulate and initiate tasks). It means that a robot may differ its LoC (capabilities) on each competence (Cohen, Shoval, Faccio, & Minto, 2021).

5.3 Method

A literature review was carried out to identify the most relevant factors to be considered in an industrial HRC system. Once the variables are defined, an SD approach is designed and runs in the software Vensim (Ventana Systems). The conceptual description and detailed model are complemented by mathematical equations of the relationships between the constants and variables. Finally, the scenarios are prospected for analysis, opening space for evaluations and policies. The sequence of activities that characterizes the research method is shown in Figure 5-1.

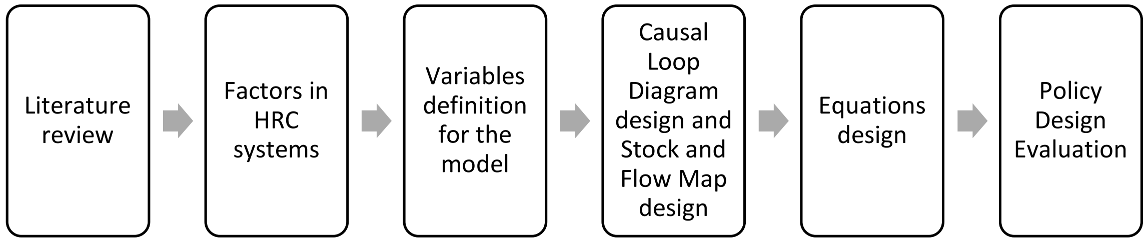

Figure 5-1. Method used in model development.

In the following section, the modeling activity is described throughout a detailed description on how the factors were arranged, and the respective diagrams are exposed.

5.4 Model

The DS modeling consists of a conceptual description based on the factors identified in the literature, and a mathematical description to allow computational simulation.

5.4.1 Conceptual Description of the System

The Causal Loop Diagram (CLD) describes the relationship between the factors or variables of a system. By organizing the factors and its relationships, the four main feedback loops are shown in Figure 5-2. The "production self-regulation" cycle describes the cause-and-effect relationships that allow the employees of the production line to adjust the work pace to meet production targets. The "learning by repetition" cycle, on the other hand, describes how daily experience leads to greater skill to execute a task, thus being a reinforcement cycle. According to the systemic theory, in real contexts the reinforcement cycles have their action limited by associated control cycles. In the CLD this occurs through the action of the "limitation due to disease incidence" cycle, which are consequences of physical and mental overload. The "mental overload reinforcement" cycle shows how the "pressure" increases mental load, which may cause sick leave, reduces task knowledge, increases the cycle time, therefore it is harder to meet production target, leading to more pressure and mental burden.

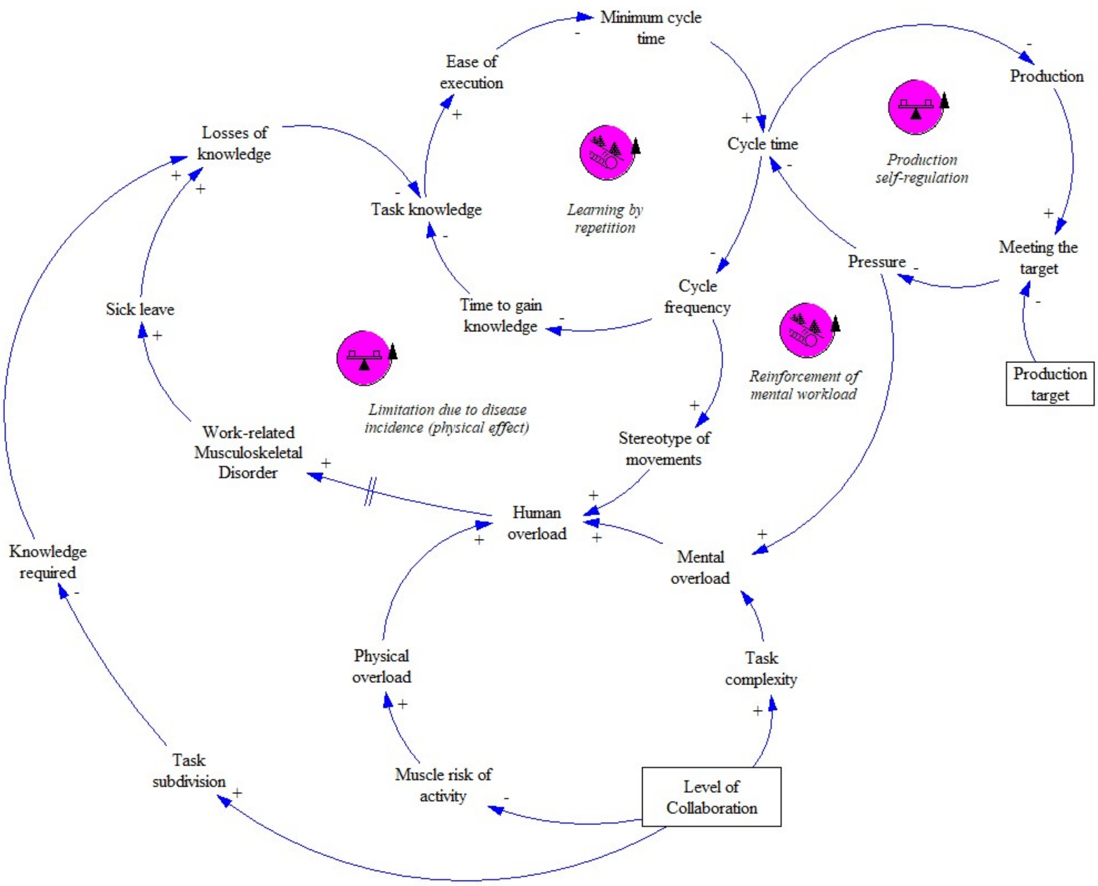

Figure 5-2. Systemic Context.

In this chapter the production target is defined by the tactical level and the described system develops trying to achieve it. Based on this context, the information is converted into a more detailed model, encompassing all the constants and variables necessary for inserting equations, computational simulation, and prospecting scenarios.

5.4.2 Detailed Model

A detailed model greatly expands the understanding established in the conceptual diagram, keeping the indicated information cycles in order to maintain the established concept itself. Therefore, the Stock and Flow Map (SFM) provides concrete details to the previously developed CLD applying a structural and mathematical model.

The structure of the subsystem that deals with the dynamics of the production subsystem was adapted from Sterman (2000) and is shown in Figure 5-3. The two stocks are “work for processing” and “work in process – WIP”. “Production rate – Pr” is defined by WIP and the “cycle time” (CT).

$$Pr = WIP/CT \,. \qquad (1)$$

In this mathematical model all WIP is processed, even under extreme theoretical conditions. Therefore, the production rate does not assume negative values.

$$Pr \in \mathbb{R} \mid Pr \geq 0 . \qquad (2)$$

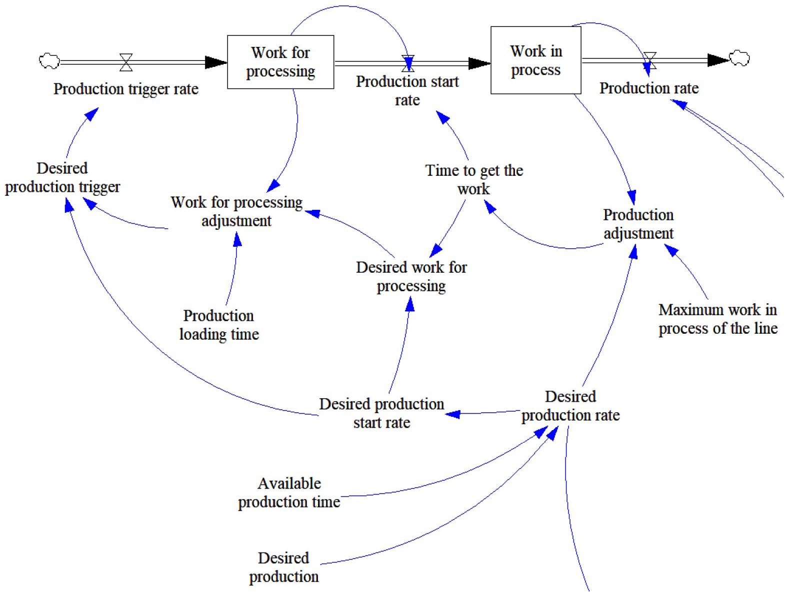

Figure 5-3. Production Subsystem.

The structure of the "cycle time" stock and its influences are presented in Figure 5-4. In real systems, workers react to possible delays and manage to reduce cycle time. This behavior is inserted by comparing the "desired production rate" with that achieved. This comparison is inserted as a "Pressure index (Pi)" that accelerates or stops the rate at which the cycle time is adjusted. The "perception time of meeting the target – PMTM" is also considered to influence the cycle time adjustment rate, which is conditioned to a "minimum cycle time – CTm" that, in the systemic context, derives from the knowledge of the task. The nonlinear behavior of the cycle time, considering that the rate at which it is obtained becomes smaller as it approaches the minimum cycle time, uses the Euler exponential relation.

$$CT = (CTm - CT_{t0}) * e^{-\left(\frac{1}{PTMT}\right)*t} * Pi . \qquad (3)$$

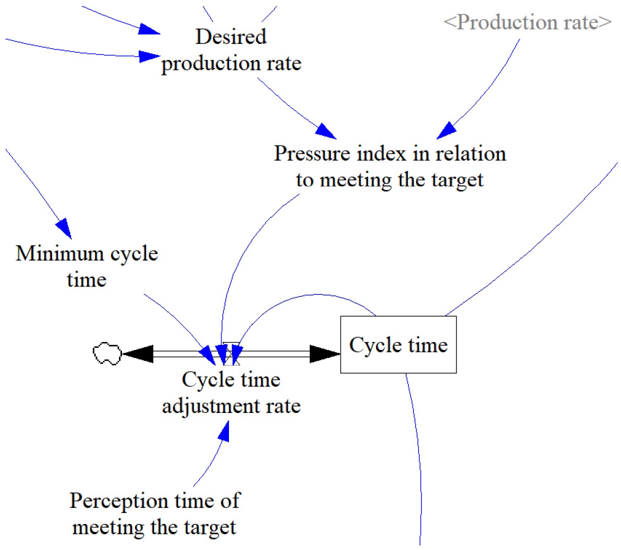

Figure 5-4. Cycle Time influences.

It is considered a structure that inserts the behavior related to employee turnover and the task knowledge index (Figure 5-5) similar to that used by Mattos et al. (2019). The “leave rate – Lr” is formulated considering both the “physical load – PhL”, the “mental load – ML”, and the average “time to disease incidence – TDI”.

$$Lr = (PhL * ML)/TDI\,. \tag{4}$$

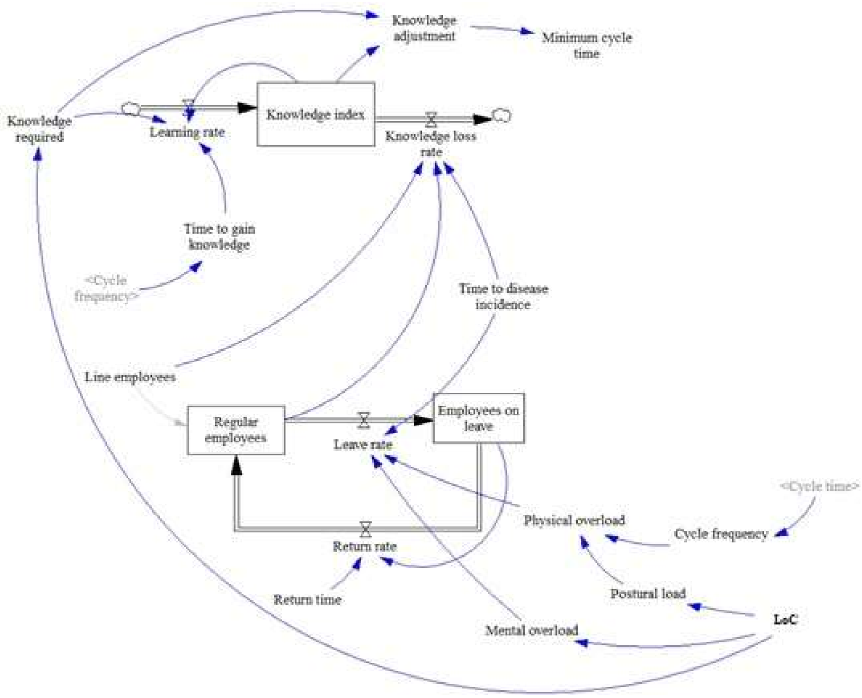

Figure 5-5. Workers and Knowledge structure.

5.5 Simulation and Prospection

The simulation and prospecting of scenarios was preceded by tests to assure the necessary reliability of the DS model to be considered useful for analysis (Forrester & Senge, 1980). The tests verified the structure, dimensional consistency, extreme conditions, and error in steady state and permanent regime.

After applying tests of the model, it was configured to prospect the scenarios to be used in the analysis. The "Euler" integration method was used. The integration increment (dt) was set to 1/5 of the value of the smallest time constant. The simulation horizon, as such analysis has a focus on operational dynamics whose effects occur in a relatively short time, was defined in a work shift (8 hours). The human workload value was weighted at 33% for mental demands and 67% for physical demands. In addition, a very important aspect of this analysis is the insertion of the LoC influences in the simulation model. In this case the insertion was done by the definition of values in ordinal scales of 5 levels. Thus, the LoC influences on mental workload, postural demand, and knowledge necessary to perform the task. The specific values used to configure the model are shown in Table 5-1.

Table 5-1. Levels of Collaboration influence on the model.

	Level of Collaboration				
	0	1	2	3	4
Mental workload	0.5	1	2	3	4
Physical workload (postural)	4	3	2	1	0.5
Knowledge	1 (100%)	0.9 (90%)	0.7 (70%)	0.5 (50%)	0.3 (30%)

As the computer simulation runs, it is possible to see the effectiveness of the feedback cycles in driving production to the goal (Figure 5-6). The pattern of behavior starts below the target, however, it grows gradually, representing a situation of adaptation and pace.

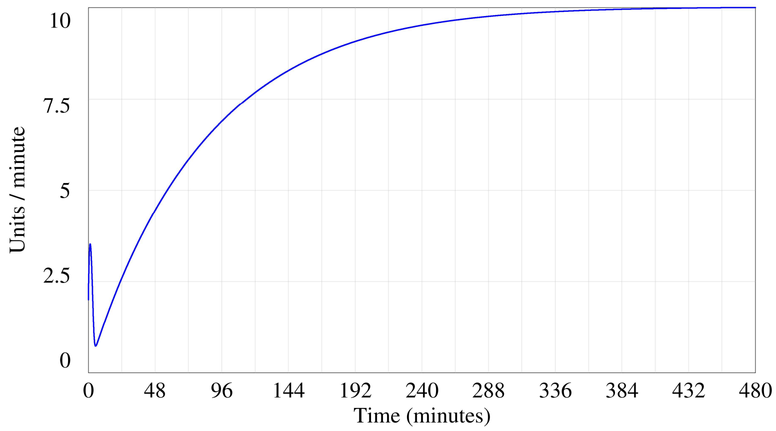

Figure 5-6. Production rate behavior through a shift time.

For a correct interpretation of the following graphics, one should compare only the last stretch of the simulation horizon as indicated in red, where the system has already reached a level of equilibrium in all LoC. In this model, the cycle time was modeled as a variable, under the influences already shown in the CLD. In general, the cycle time decreases as the production line is able to adjust production to the target. This is due to increased knowledge in terms of the ability to carry out the task. In Figure 5-7 it presents the evolution of the cycle time over the simulation horizon time together with a third axis (robotic), which proves to be very useful for the interpretation of the system. It shows little improvement between the condition of the production line between level 0 and a level 1. Level 2, in terms of the operationalization of the production line, is shown to be the best condition, since the cycle time easier meet the goal. However, levels 3 and 4 showed worse results (in terms of operationalization) compared to level 0.

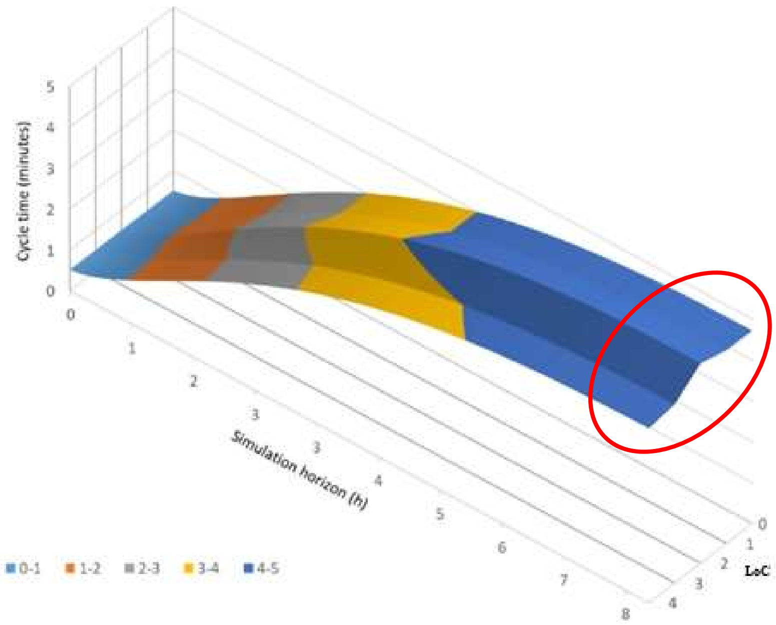

Figure 5-7. Variation of cycle time for different LoC.

As shown in Figure 5-8, the most favorable scenario to avoid the incidence of occupational diseases, which leads to employees on leave, corresponds to the highest level of robotic assistance (30.4% lower than level 0). Although this level still returns a greater frequency of cycles (due to the reduced cycle time) and the performance of mental workload, the reduction in postural load seems to compensate for these factors.

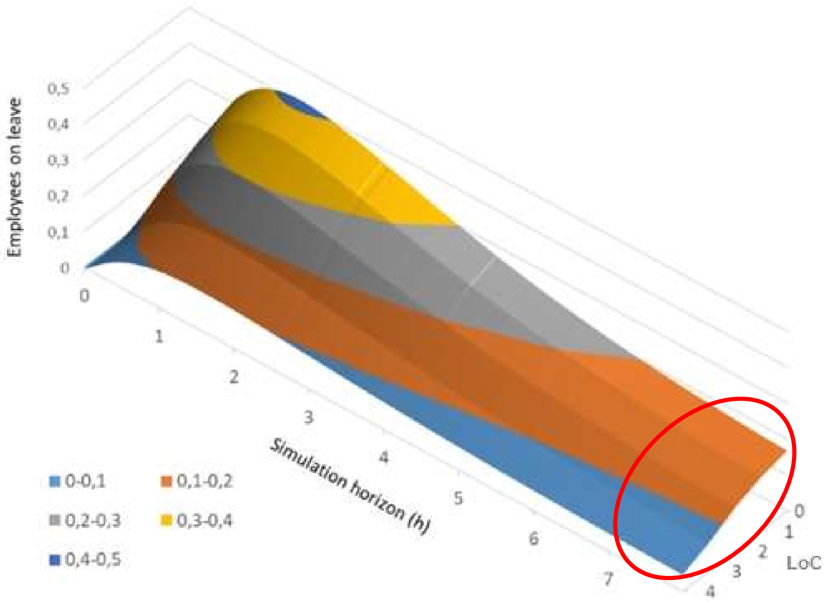

Figure 5-8. Variation of employees on leave for different LoC.

It demonstrates that inserting an HRC system is complex, and both physical and mental workloads may affect the leave rate, which significantly change the prospective scenarios.

It was observed that the existence of a cognitive load can generate counterintuitive effects on the system's behavior. Thus, expanding the model for its practical application consists of selecting ergonomic tools for the quantification of the levels of physical and mental workload that can be applied in an industrial HRC system.

5.6 Conclusion

The simulations showed that the incidence of occupational disease is significantly reduced with the inclusion of an industrial HRC system. In the scenarios prospected by this preliminary model, the reduction was up to 30.4%. On the other hand, it does not mean that higher LoC always lead to higher levels of productivity and safety. It can be found more often than not that intermediate LoC fits better to solve a problem regarding HRC systems. A correct understanding of a system is achieved by modeling and prospecting scenarios, specially looking for counter intuitive effects.

This model can be applied to a practical case where the scenarios could be used by managers for decision-making. However, there are two main points where this chapter is further developed in this thesis: (i) exploration of how mental load occurs by evolving the structure that inserts the behavior of such load in the simulation model (e.g., Jafari et al. (2019) developed it specifically using SD to assist such exploration; (ii) application of ergonomic tools to quantify the levels of physical and mental workload that can be applied in the practical context (e.g., RULA method for physical workload (Middlesworth, 2019) to assess postures, and NASA-TLX questionnaire for mental workload that classifies the load perceived by operators (Hart & Staveland, 1988).

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CHAPTER 6 | Decision-making framework for implementing safer Human-Robot Collaboration workstations: System Dynamics modeling

Abstract. HRC systems are often implemented seeking for reducing risk of WMSD development and increasing productivity. The challenge is to successfully implement an industrial HRC to manage those factors, considering that non-linear behaviors of complex systems can produce counterintuitive effects. Therefore, the aim of this chapter is to design a decision-making framework considering the key ergonomic methods and using a computational model for simulations. It considers the main systemic influences when implementing a collaborative robot (cobot) into a production system and simulates scenarios of productivity and WMSD risk. In order to verify whether the computational model for simulating scenarios would be useful in the framework, a case study in a manual assembly workstation was conducted. Results show that both cycle time and WMSD risk depend on the LoC. The proposed framework helps deciding which cobot to implement for safer operation in a context of industrial assembly process. System dynamics is used to understand the actual behavior of all factors and to predict scenarios. Finally, the framework presented a clear roadmap for the future development of an industrial HRC system, drastically reducing risk management in decision-making.

6.1 Introduction

The recent advance in industrial technology is dealing with complex problems: to increase productivity without neglecting human factors; to look for specific improvements in spite of considering the whole system dynamics; and to solve today's problems without creating a new one to be addressed in the future (Borges et al., 2021). The implementation of an HRC system is often aimed at reducing WMSD at the same time that increases production, by combining the skills of both humans and robots (Peternel, Kim, Babic & Ajoudani, 2017; Roveda, Haghshenas, Caimmi, Pedrocchi & Tosatti, 2019).

Workers are daily exposed to physical and mental workplace hazards (Robertson, Jayne, & Oakman, 2021), especially in assembly workstations in industry (Battini, Delorme, Dolgui, Persona, & Sgarbossa, 2016). Ergonomic risks lead to absenteeism due to WMSD (Bokhorst et al., 2008; EU-OSHA, 2020). In order to mitigate those issues, a possible ergonomic intervention is to implement an industrial HRC system, which combines both robot and human skills. Moreover, a cobot performs the task like a co-worker, with no physical barriers to help achieving a goal (Gervasi, Mastrogiacomo & Franceschini, 2020). Being a co-worker, it is also expected to increase productivity (Vicentini et al., 2020). The implementation of an industrial HRC system is not simple and there are many organizational factors to consider (Badri, Boudreau-Trudel, & Souissi, 2018; Charalambous et al., 2015). Moreover, there are critical technical issues, ergonomics, safety, and economic aspects to consider when evaluating scenarios with a cobot (Gualtieri, Rojas, Garcia, Rauch, & Vidoni, 2020; Roveda, Spahiu & Terkaj, 2019). By making a correct assessment of the current workstation it is possible to run a simulation model (Mattos, Ariente Neto, Merino, & Forcellini, 2019), which brings more data for understanding the system and ultimately for a correct decision.

Therefore, the aim of this chapter is to develop a decision-making framework for implementing HRC systems. The contribution highlights of this chapter follow: a framework to decide which collaborative robotic system to choose; a system dynamic model that considers LoC, physical and mental workloads with simulation of scenarios for absenteeism and productivity; and a case study applying a roadmap to reduce risk management in decision-making. The system dynamics model is limited to the boundaries chosen, which excludes other variables that might be useful depending on the characteristics screened for a specific workplace. The article is structured as follows:

- An introduction to the fundamental concepts related to the problem being addressed, namely: HRC, ergonomics, and system dynamics.
- A decision-making framework proposal, starting with the problem definition, followed by an assessment of the current workstation, a computational model of the system, the evaluation of possible solutions, and the final decision regarding an industrial HRC system.
- A case study applying the aforementioned framework in a manual assembly workstation that intends to implement an industrial HRC.

6.2 Fundamental concepts

6.2.1 Human-Robot Collaboration

The fourth industrial revolution is characterized by smart and autonomous systems (Gervasi et al., 2020). Cobots allow workstations without barriers, and its implementation is a potential solution when planning to improve workstation conditions. This solution combines typical robot's capabilities (accuracy, speed, and repeatability) with human skills (adaptability, dexterity, and perception) aimed at achieving a common goal (Salvendy, 2012). According to Bauer et al. (2016), there are five LoC with increasing complexity, competences, and cost: Level 0 (cell), Level 1 (coexistence), Level 2 (synchrony), Level 3 (cooperation), and Level 4 (collaboration). The design of HRC workstations has to integrate some requirements in order to propose task allocations (Pini, Leali, & Ansaloni, 2015; Tan et al., 2009): (Human) posture, strength, biomechanics and cognition; (Robot) joints position, velocity, acceleration and sensors; (Human and Robot interaction) force or feedback force; and (Process) manufacturing goals, such as cycle time and quality. Moreover, when designing an HRC system and considering ergonomic aspects, it is expected to reduce human workload, WMSD risk factors, and production costs. Therefore, many of the current workstations should consider the implementation of a cobot to work in a safe, ergonomic, and efficient way. Accordingly, a successful implementation of a HRC system depends on considering ergonomics (Charalambous et al., 2015).

6.2.2 The role of ergonomics in the workstation transformations

Ergonomics is the discipline that studies the relationship between man and work, seeking for adaptation of the workstation environment for the worker to carry out his activities (Stanton, Hedge, Brookhuis, Salas, & Hendrick, 2004). New technologies and interventions in industry increases environment complexity, which means that ergonomics should be treated using a systematic view (Salmon, Walker, Read, Goode, & Stanton, 2017). Organizations often do not get the most ergonomic benefits when they introduce new technologies (Charalambous et al., 2015). It is confirmed by Busch, Toussaint, & Lopes (2018) that optimizing simultaneously task allocation while taking into account ergonomic aspects improves the efficiency and acceptance. Also, the concept design in Changizi, Dianatfar, & Lanz (2019) considers human mental and physical viewpoints at the same time by proposing a hand-guiding on the robot for the users to have control over the system, having the robot as a helper instead of a robot giving an object. A systemic view that predicts scenarios regarding ergonomics and productivity is needed, and not considering ergonomics in HRC systems may present undesired effects (Green et al., 2008).

6.2.3 System Dynamics

System dynamics is a method to navigate the complex systems. It is grounded in the theory of nonlinear dynamics and feedback control developed in mathematics, physics, and engineering to understand a system's behavior (Sterman, 2004). Through this method it is possible to design, to model, to simulate, to understand, and finally to make good decisions in complex systems taking both short- and long-term behavior into consideration. These systems exist in an environment within boundaries and are characterized by their structure, elements that interact, processes, goals, inputs, and outputs. As seen in Mattos et al. (2019), computer simulations are controlled experimental environments in which different possibilities can be tested without investing a great amount of resources before evaluating and deciding.

The interest in this topic has grown recently as stated in Karsh et al. (2014) that ergonomic study should always involve a systemic view, with any analysis or interventions considering the context as a whole. It was found in Shire, Jun, & Robinson (2018) that using system dynamics has potential to increase safety in complex systems that cannot be achieved with traditional approaches (Gualtieri, Rauch, & Vidoni, 2021). Similarly, ergonomics is also of crucial importance in the implementation of an industrial HRC. The three ergonomic dimensions have been considered in Ender et al. (2019) when designing workstations for manual production and maintenance processes. In McDonald, Bonaventura, & Ullman (2011) employees suffering from injuries result in worse productivity and quality of products which leads to losses and indirect costs. Indirect costs like absenteeism are often difficult to measure and are excluded from production costing models. A literature review found ergonomic frameworks with the following characteristics: focusing on the physical assessment (Colim et al., 2020); an integrated framework addressing both physical and psychological levels (Sadrfaridpour et al., 2016); an agent-based model included ergonomics in terms of assessing risk levels, considering how pain and fatigue affect performance (Sammarco et al., 2014); an optimized hierarchical model to improve production time and ergonomics for decision-making (Pearce et al., 2018); and insights on the productivity and its ergonomic impact on workers (Farid & Neumann, 2020). It demonstrates that a framework is needed in order to avoid injury, poor quality, low production, and to decrease costs in complex systems.

6.3 Decision-making framework

A logical decision-making process was built analyzing the current situation, evaluating the available possibilities, and finally deciding what to do based on information about the system. This methodology was chosen to create a complete roadmap framework to be used together with system dynamics. It was divided in the following phases: (i) assessment of the current workstation by applying methods from the three ergonomic dimensions (physical, cognitive, and organizational) and collecting production data; (ii) computational modeling of the key factors of the system considering different LoC; (iii) simulation and prospection of scenarios regarding absenteeism and productivity when inserting a cobot into a production system; and (iv) technical, ergonomic, safety, and economic evaluation for a better decision-making.

6.3.1 Problem Definition

In the cases where this framework can be useful, usually the problem is related to both absenteeism due to WMSD and productivity. The reason is simple: by introducing an industrial HRC system, it is expected to reduce the human efforts regarding postures and repetitiveness. Also, by including automation into the production line, it is expected to increase productivity. Therefore, the framework is designed for those who need to choose what kind of cobot to install or what LoC fits better in the long term of this cooperation.

6.3.2 Ergonomic Assessment

Based on the characteristics of an HRC workstation, ergonomic methods from the three ergonomic domains have been used to assess the risks. The framework provides guidance, but does not suggest a strict set of tools, allowing more adaptability for the practitioner who must navigate within a particular context. Four physical risk levels and two mental risk levels were defined by the simulation modelers in order to weight the overall human workload. It is suggested to use at least one from each of the following domains:

6.3.2.1 Organizational

Ergonomic methods to assess organizational factors are mandatory to allow building the causal loop diagram (CLD) (Mattos et al., 2019), a diagram that represents the actual system under study. There are two main options to choose for a complete workstation description, according to preferences:

- Ergonomic Analysis of Work (Guérin, Laville, Daniellou, Duraffourg, & Kerguelen, 2007) – an observational screening method to assess the workstation. It is divided into five stages: demand analysis, task analysis, activity analysis, diagnosis, and recommendations. By applying this method, it is possible to identify the main variables of a system and their interconnections in order to build the CLD of a dynamic system.
- Ergonomic Workplace Analysis (EWA) / Finnish Institute of Occupational Health (FIOH) (Ahonen, Launis, & Kuorinka, 1989; Ketola, Toivonen, & Viikari-Juntura, 2001) – a time-based checklist observational method to assess the main risk factors of the workstation. It is divided into 14 topics: workspace; general physical activity; lifting tasks; work postures and movements; risk of

accident; work content; restrictiveness; workers' communication; decision-making; work repetitiveness; level of required attention; lighting; thermal conditions; and noise.

6.3.2.2 Physical

The physical workload is directly related to high force loads, awkward postures, and repetitive movements, which lead to WMSD and absenteeism (Siong, Azlis-sani, Hisyamudin, Nor, & Nur, 2018). To understand the system, this framework suggests choosing at least one of the ergonomic methods in this domain to assess the risks related to the workstation. The method should be chosen according to preferences and the specific characteristics of an assembly task:

- Rapid Upper Limb Assessment (RULA) (Middlesworth, 2019) – an observational ergonomic tool that considers biomechanical and postural load requirements of job tasks. It is a good and widely used method to assess physical workload, except for not considering the duration of exposures.
- Ergonomic Assessment Worksheet (EAWS) (Schaub, Caragnano, Britzke, & Bruder, 2013) – a screening tool developed for the automotive industry. The method combines aspects of manual load handling and assesses the risks of body postures, action forces, manual handling, and upper members.
- National Institute for Occupational Safety and Health (NIOSH equation) (Waters, Putz-Anderson, & Garg, 1994) – a method to assess the risk of low-back disorders in jobs with lifting tasks. It is based on biomechanical, physiological, psycho-physiological, and epidemiological data. It is a well-documented method.
- Key Indicator Method for Manual Handling Operations (KIM-MHO) (BAuA, 2019) – an observational method often used for assembly tasks. It aims to evaluate the probability of physical overload and possible consequences of WMSD.
- Revised Occupational Repetitive Actions checklist (OCRA) (Colombini, Occhipinti, & Álvarez-Casado, 2017) – a method to screen the risk associated with upper-limbs in repetitive tasks. This method takes into account the recovery periods.
- Nordic Musculoskeletal Questionnaire (NMQ) (Kuorinka et al., 1987) – a standardized questionnaire used to evaluate and to characterize musculoskeletal symptomatology perceived by workers, considering nine body regions. Perceived pain intensity is assessed using a numerical scale for each of the body regions.

- Electromyography (EMG) (Battevi, Pandolfi, & Cortinovis, 2016; Cifrek, Medved, Tonkovic, & Ostojic, 2009) – a direct risk measurement technique to deal with physiological parameters of the human body when performing dynamic tasks. It allows identifying the muscle fatigue index, which is the cause of WMSD, by capturing the bioelectric signal emitted during muscle contractions.

Each one of the physical workload methods is based on their own scale to assess the physical risk of a task. These scales are usually named as acceptable risk, low risk, medium risk and high risk. As this framework intends to use the risk level in a simulation model, the different output values from the selected physical methods were converted into a numerical scale of four physical risk levels. According to the aforementioned reference, Table 6-1 presents the four suggested physical risk levels that can be obtained for each ergonomic method chosen.

Table 6-1. Physical risk levels based on the output scores of each ergonomic method.

Physical Risk Level	Meaning	RULA scores	EAWS points	NIOSH lifting index	KIM-MHO points	OCRA checklist	NMQ Borg scale	EMG % MVC
I	Acceptable risk	1 or 2	0 to 25	< 1	< 20	< 7.5	0	0 to < 1
II	Low risk	3 or 4	26 to 50	1 to < 2	20 to < 50	7.6 to 11.0	1 to 3	1 to < 10
III	Medium risk	5 or 6		2 to ≤ 3	50 to < 100	11.1 to 22.5	4 to 6	10 to ≤ 14
IV	High risk	7	> 50	> 3	≥100	≥ 22.6	7 to 10	> 14

6.3.2.3 Cognitive

Mental workload is often ignored when assessing the risks related to a workstation. However, many authors emphasize the importance in considering this factor in a system (Fruggiero et al., 2018; Robertson et al., 2021; Sgarbossa, Grosse, Neumann, Battini, & Glock, 2020), especially in the long term. There are three main methods to choose in this domain:

- NASA Task Load Index (NASA-TLX) (Hart & Staveland, 1988) – a widely applied questionnaire used to assess mental workload, including work systems with a high level of complexity. It evaluates mental demand, physical demand, temporal demand, effort, frustration, and performance. A numerical scale is used to assess the workload perceived by the worker for each of the six items.
- Subjective Workload Assessment Technique (SWAT) (Reid & Nygren, 1988) – it was originally designed to assess aircraft cockpit workload. It is divided in two phases: scale development and scale scoring. The three dimensions measured are: time, mental effort, and psychological stress.

- Electrodermal Activity (EDA) (Choi, Jebelli, & Lee, 2019) – a technique to identify changes in the skin's electricity by wearable sensors. It may be employed for assessing emotional states and to understand the worker's mental status. EDA is divided in electrodermal response (EDR) that reflects short-term stress, and electrodermal level (EDL) is more related to risk perception and a relevant indicator of long-term stress.

Similarly, to the physical workload, as input to the simulation model, the different output values from the selected mental methods were converted into a numerical scale. According to the aforementioned references, Table 6-2 presents the two suggested mental risk levels that can be obtained for each method chosen.

Table 6-2. Mental risk levels based on the output scores of each method.

Mental Risk Level	Meaning	NASA-TLX overall workload	SWAT value	EDA EDR's mean value
I	Low risk	0 to < 60	0 to < 60	Below 0.5
II	High risk	60 to < 100	60 to < 100	Above 0.5

6.3.3 Production data

The current data of the production line are necessary to model the dynamics of a system. In this regard, based on literature (Mattos et al., 2019; Sterman, 2004), the most important factors suggested by this framework are:

- Production goals – number of pieces to be assembled in a period of time.
- Takt time – assembly duration time needed to match the production goals.
- Cycle time – the time it takes to complete one assembly.
- Absenteeism due to WMSD – the sick leave rate due to musculoskeletal issues.
- Number of workers – the sum of workers in the production line.

It means that a correct assessment of production is sufficient with the above factors. However, for understanding the dynamics of an actual system other factors may be useful as well (e.g., gender, age, seniority, previous injuries, or illnesses).

6.3.4 System Dynamics

This framework suggests modeling the system under study using both ergonomic and production data. Modeling is divided into conceptual definition, structural description and simulation. It aims at representing the most important factors and their interconnections with focus on solving a problem. In this case the context also includes the insertion of a cobot considering different LoC into the system to evaluate scenarios. As a result, it is expected to maximize the worker's well-being and system performance. An example of conceptual description, the CLD with the above-mentioned factors are represented in Figure 6-1. In the conceptual definition four information feedback cycles are relevant: "production self-regulation", "learning by repetition", "limitation due to disease incidence", and "reinforcement of mental workload".

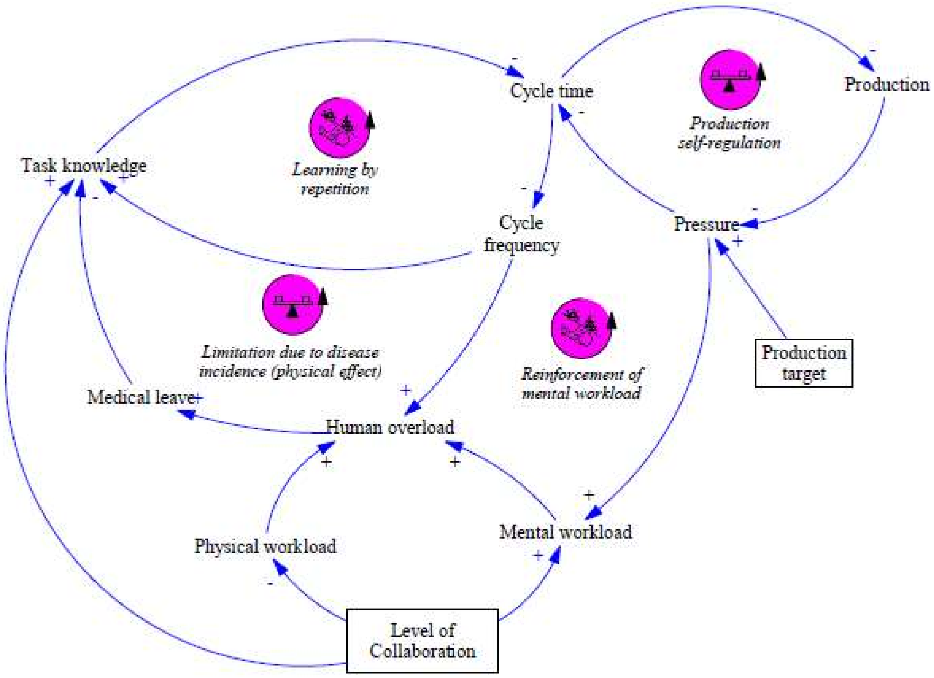

Figure 6-1. Causal Loop Diagram for an industrial Human-Robot Collaboration system.

As the problem is related to productivity and absenteeism due to WMSD, the hypothesis to be considered is at what extent the robot will collaborate. It is widely demonstrated that the intervention of an industrial HRC system increases productivity and decreases ergonomic efforts (Colim et al., 2021; El Makrini et al., 2019; Pini et al., 2016). Moreover, there are different competence levels for a cobot (Cohen et al., 2021) to be chosen, which are very much related to the LoC. Which LoC is best for the current situation is what a simulation model can answer.

Therefore, by applying a structural and mathematical model, the Stock and Flow Map (SFM) is needed to understand what was established in the conceptual diagram, maintaining the cycles and the established concept itself. There are many examples of SFM in the literature that can be adapted to the current system, however, it must be tested and calibrated according to the situation. Table 6-3 presents the description of competences regarding safety and ergonomics, as well as the influence of LoC on the model.

Table 6-3. Description of competence levels with their influence on the model.

System	Level of Collaboration				
	0	1	2	3	4
Safety and human support of a cobot (Cohen et al., 2021)	Current workstation without cobot.	ISO/TS 15066 Safety-rated monitored stop.	ISO/TS 15066 Hand-guiding.	ISO/TS 15066 Speed and separation monitoring.	ISO/TS 15066 Power and force limiting
		Cobot performs repetitive, and/or dangerous tasks, and sounds an alarm in an emergency.	Cobot performs ergonomically challenging tasks: dirty, hot, humid, and noisy environment. Cobot issues safety warnings and suggests help only in emergencies.	Cobot brings tools or parts next to the operator and takes them away. Cobot issues reminders, and draws attention to evolving situations.	Cobot holds and/ or manipulates the tool or work piece. May initiate tasks: 'let me hold it'. May suggest help in extreme cases.
Mental	Mental workload increases with the complexity of the task (Fruggiero et al., 2018; Pini et al., 2016).				
Physical	Physical workload decreases when cobot assumes the tasks related with loads and repetitiveness (di Nardo et al., 2015; Rücker et al., 2019).				
Knowledge	Knowledge of the task can assume different values depending on the specific workstation (Mattos et al., 2019).				

The system dynamics simulation phase is reserved to prospect scenarios for analysis of different possibilities. It aims at understanding the system to establish risk indicators, to propose organizational changes and ergonomic interventions, which finally support management evaluation of the system performance.

6.3.5 Management evaluation and decision

The evaluation process by the management is critical in deciding whether to include a robot in the system. After analyzing the prospected scenarios, there are other management aspects to consider. The minimal phases to be considered are shown in Figure 6-2.

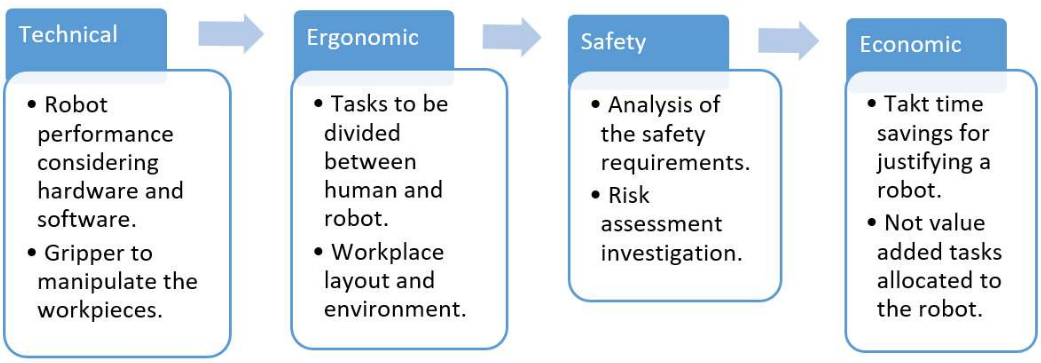

Figure 6-2. Managerial evaluation analysis.

The technical evaluation considers the technologies available (robot arm, gripper, sensors), the new workstation configuration (shop floor space), computational systems to be integrated (interfaces, hardware and software limitations), and even the experience and training of workers.

Technical issues might be a critical variable when implementing a cobot. Ergonomic evaluations were already discussed during the first assessment.

Especially when deciding which tasks are to be allocated to the worker, the new workstation also needs special ergonomic considerations. Postures (workstation layout), frequency of repetitive actions, workloads, and time pressure as well as safety requirements. The new productivity goals are limited by ergonomic and safety issues. Therefore, when evaluating economics, every variable is important. The economic evaluation might be estimated considering the non-value added tasks that will be automated (Gualtieri et al., 2020), as these tasks usually consume time and production resources. Therefore, it is possible to compare the savings with the investment. Another way to manage the economic evaluation is formulated in Cohen et al. (2021), where the cobot savings percentage of the manual takt time should be higher than the minimal required, saving to justify implementing a cobot in the system.

There are other aspects that could be considered when evaluating the inclusion of a cobot for example, the product and process quality, which can be evaluated by the level of process variability and its standardization level (Gualtieri et al., 2020). A managerial decision is based on the available information. In order to avoid making decisions based on half information or mental models, this framework presented a logical roadmap to bring relevant data to be considered and help deciding at this last stage of the framework:

- Summarizing the most important factors of the current situation;
- Including the system dynamic model is key to understanding the whole system;
- Considering the organizational recommendations from the simulation and prospection model;
- Relying on the technical, ergonomic, safety, and economic evaluations;
- Defining the new productivity and absenteeism goals.

The managerial team decides which cobot to implement. As the introduction of a new technology, it is important to have such a global approach. Figure 6-3 summarizes the proposed roadmap for a decision-making in HRC systems.

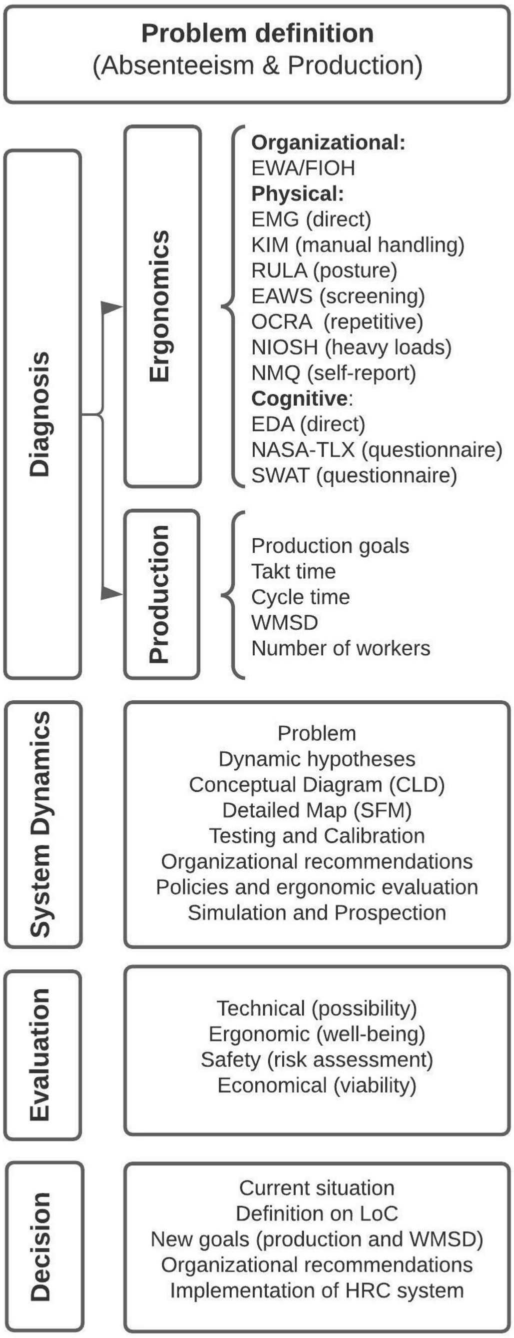

Figure 6-3. Phases of the developed framework.

6.4 Case Study

A workstation for manual assembly of electrical components in Portugal was planning to incorporate an industrial HRC system. According to the company's information, the workstation deals with recurrent absenteeism due to WMSD. Therefore, this framework was applied in order to help decision makers, which system to choose. Figure 6-4 presents the steps towards the objectives of this case study.

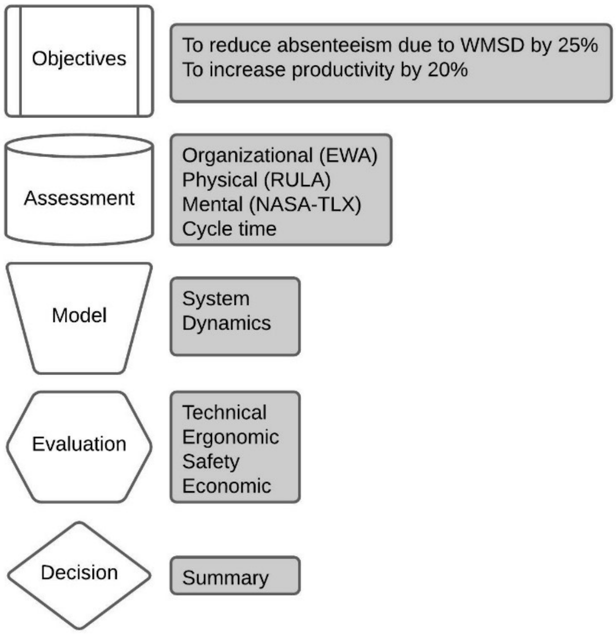

Figure 6-4. Applied framework for ergonomic assessment in a workstation with an HRC system.

6.4.1 Objectives

Absenteeism is often the starting point of ergonomic interventions in a production line, as it directly impacts in human being as well as productivity (Kim et al., 2019). According to the company, the main goal is to reduce absenteeism due to WMSD by 25% and simultaneously increase productivity by 20%. In order to prospect scenarios with HRC systems, a computational model was used in this case study. Therefore, a workstation assessment regarding ergonomics and productivity was carried out to design and to feed the model.

6.4.2 Workstation Assessment

6.4.2.1 Ergonomic Work Analysis

Direct observation was performed on the workstation under analysis in order to characterize the environment, the process, and the main variables as well as their interconnections. The most critical WMSD risk factors were identified, such as awkward postures and repetitive tasks. Therefore, a replica-workstation for manual assembly of electronic components was built considering the same dimensions in order to replicate body ranges and postures.

The workstation layout presented in Figure 6-5 and consists of reaching pieces on both the left and right sides at different heights, and to assemble them in the center (in front of the worker). Thus, the characteristic movements are vertical reach movements at shoulder level, sometimes with lateral flexion of the trunk and displacement in steps to the side.

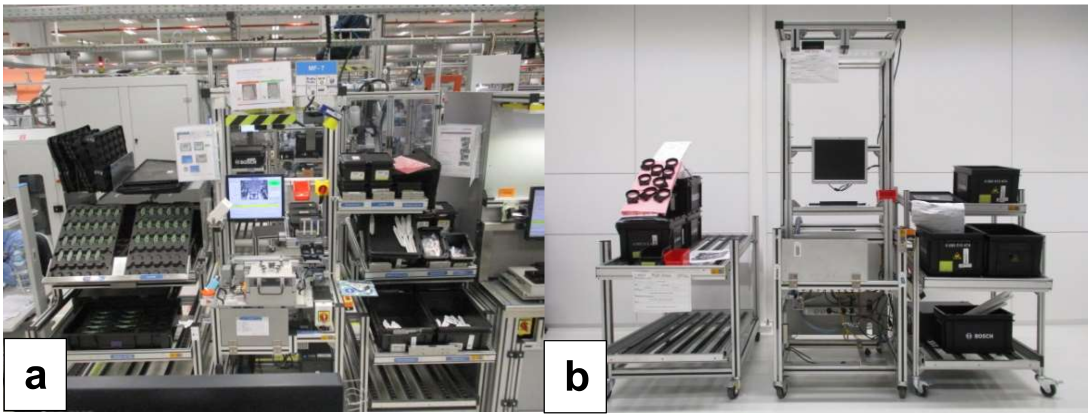

Figure 6-5. Workstation layout: a. Original; b. Replica.

The piece to be assembled consists of seven components which are presented in Figure 6-6a. From P1 to P3 the components are on the left side, from P4 to P6 on the right side, and P7 is placed in front of the worker (close to the assembly table).

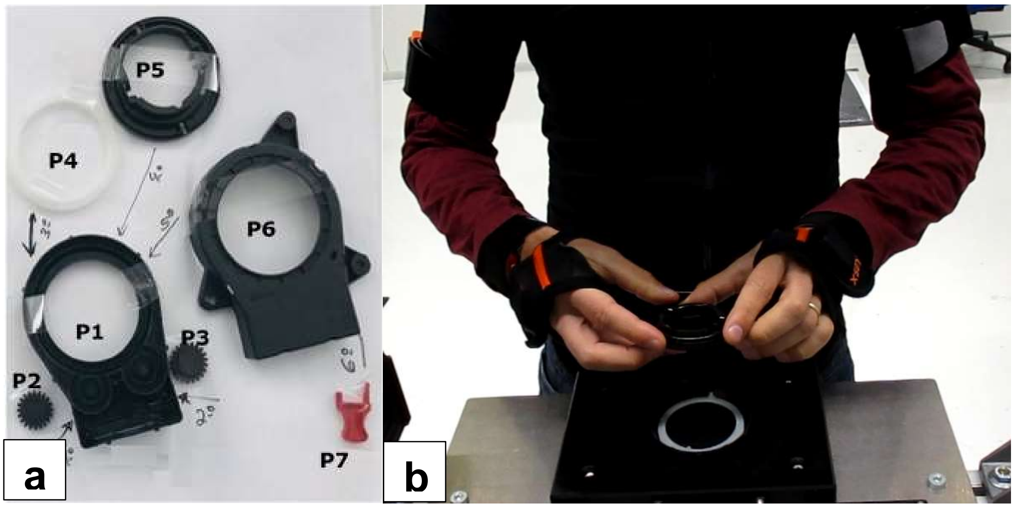

Figure 6-6. Assembly piece and sequence: a. Components; b. Manual handling.

In order to obtain data from all different dimensions of the Portuguese population, the worker's sample was divided into three classes of percentiles. In total, six workers were chosen (one female and one male from each of the percentile classes presented in Table 6-4). The anthropometric dimension "stature" was the dimension used as a reference (Barroso, Arezes, da Costa, & Miguel, 2005).

Table 6-4. Stature percentile classes for female and male.

Percentile	Female (mm)	Male (mm)
[5 – 35[	1456 – 1539	1565 – 1660
[35 -65[	1540 – 1589	1661 – 1718
[65 -95[	1590 – 1673	1719 – 1814

6.4.2.2 Physical workload assessment

RULA was the ergonomic method chosen for physical workload assessment. Workers were equipped with wearable sensors and RULA score was obtained automatically with an algorithm developed by Xsens®. The algorithm estimates the percentage of time that the subject was in each of the four risk levels defined by RULA during the task. The procedure involved the following steps: sociodemographic data (age, height, weight) of the six workers were collected; body dimensions were collected as input to the software; biomechanical data were collected in real time of work activity (Merino, Mattos, Guimarães, & Merino, 2019) at a frequency of 120 Hz (Silva et al., 2020); data were transmitted wirelessly to a computer loaded with a software that allows the movements to be observed, recorded and analyzed; the speed of the movements was defined by each participant, according to their individual abilities; workers performed the task continuously during six cycle times. Figure 6-7 shows the sensors placement that was followed by calibration and recording using the Xsens® MVN software. Figure 6-8 shows workers performing the assembly tasks with the sensors capturing movements.

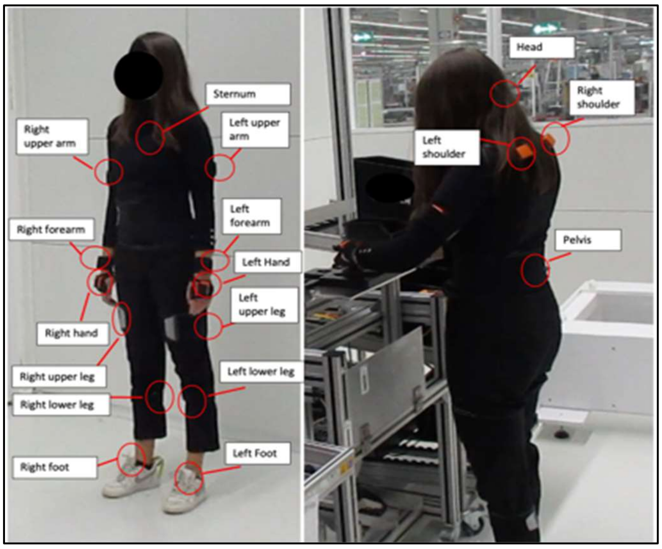

Figure 6-7. Sensor's placement in the body.

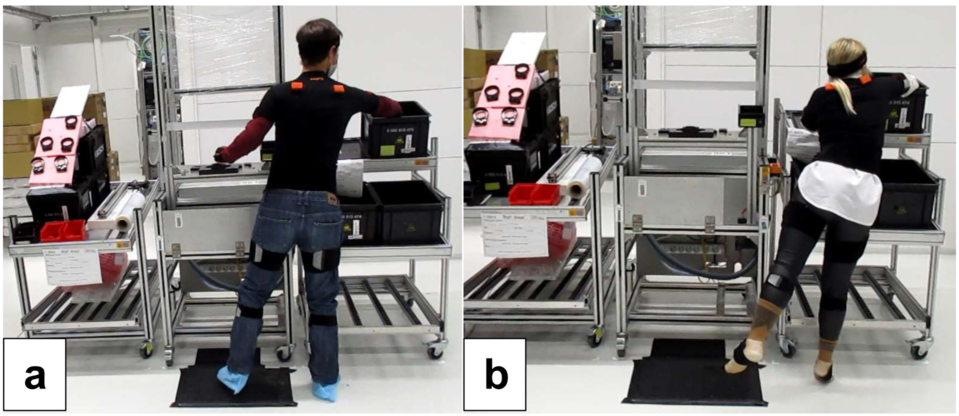

Figure 6-8. Assembly task with sensors for obtaining RULA scores: a. Highest percentile; b. Lowest percentile.

The average percentages of time exposure obtained for each risk level were the following: 0.2% acceptable, 77.5% low risk, 19.3% medium risk, and 3.0% high risk, which was considered RULA = 4. Therefore, according to Table 6-1, the model used “Physical Risk Level II” for simulation.

6.4.2.3 Mental workload assessment

The ergonomic method chosen for mental workload assessment was NASA-TLX (Hart & Staveland, 1988). The questionnaire was applied to the six volunteers after a work shift. The procedure was: to explain the definition of the 6 items (mental demand, physical demand, temporal demand, performance, effort, and frustration); to ask the workers to choose on a scale their own perception of the task; and finally, to ask each worker to choose the item they consider most relevant for each of the fifteen pairs of items presented. The average results are shown in Figure 6-9b. The overall workload is 44, which means “moderate”, and no item is especially critical. It was classified as low mental risk level according to Table 6-2. Therefore, the model considers “Mental Risk Level I” for simulation purposes.

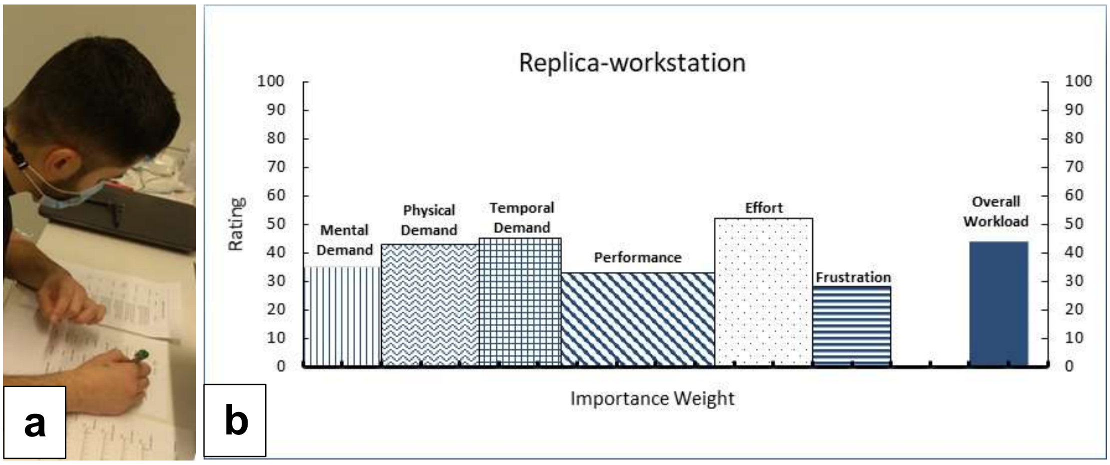

Figure 6-9. NASA-TLX results for the replica-workstation: a. Questionnaire application; b. Results.

6.4.2.4 Cycle Time

Time study is used to determine the time required by a qualified and well-trained person working at a normal pace to do a specified task (Barnes, 1980). A digital stopwatch was used to record 20 minutes of task executions. The average cycle time in the replica-workstation was 23.10s.

The results obtained in the assessment phase are summarized in Table 6-5 to be used in the modeling and simulation phases.

Table 6-5. Summary of assessment results to be modeled.

EWA	RULA	NASA-TLX	Cycle Time
Workstation variables	Risk Level II	Risk Level I	23.10s

6.4.3 Modeling

The use of system dynamics allows the systemic contextualization of the factors assessed in the workstation, a mathematical description of their interrelationship, and the prospection of scenarios in non-linear relationships. A system dynamic was designed in Vensim software (Ventana Systems) to model the whole environment (See Appendix). The production system is based on the model described by Sterman (2004) (e.g., "work in process", "production start rate" and "production rate"). Furthermore, the construction of the model is adapted to the characteristics of the context under study. In this sense, the “work for process” is a complement factor inserted along with its input rate and influence variables. The structure of employees’ dynamics and its reflection on the production system follows an analogous context (Mattos et al., 2019), in which the same phenomenon is analyzed. The model calibration was performed aiming to drive the system’s behavior to values close to those observed and recorded in the real system. Therefore, certain equations receive an adjustment constant (e.g., equation Time to gain Knowledge). The “Time to gain Knowledge (TK)” is inversely proportional to the “Cycle Frequency (CF)” since frequent cycles (with greater repetition) result in less time to gain knowledge (faster learning through repetition), being mathematically formulated as: TK = constant/CF. The constant value calibrated in this study was 480, resulting in TK = 480/CF. The variables “Mental Overload” (MO), “Physical Overload” (PO), and “Knowledge Required” (KR) were entered as a function of the LoC (See Appendix). The variable “Postural Requirement” (PR) is an inter-mediate variable between the LoC and PO for the model to support the insertion of values obtained from any ergonomic method chosen to assess physical effort. The integration increment was set to 1/5 of the value of the shortest time constant. Since the analysis was focused on operational dynamics whose effects occur in a relatively short time, the simulation horizon was defined in a work shift (8 hours). The total human workload value was subjectively weighted by the modelers at 33% for the mental demands (Risk Level I) and 67% for the physical demands (Risk Level II), which means that physical factors were considered twice more critical in the current study. In addition, a very important aspect of this analysis is the insertion of the LoC influences in the simulation model. In this case, the insertion was done by the definition of values in ordinal scales of five levels, in which level 0 of collaboration means a workstation without the robot, and level 4 means maximum collaboration. As LoC influences on mental workload, postural demand, and knowledge necessary to perform the task, the values defined by the modelers to configure the model are shown in Table 6-6.

Table 6-6. Description of LoC with their influence on the model.

	Level of Collaboration				
	0	1	2	3	4
Mental	0.5	1.0	2.0	3.0	4.0
Physical	4.0	3.0	2.0	1.0	0.5
Knowledge	100%	90%	70%	50%	30%

The relationship among LoC, cycle time and sick leaves over the simulation horizon is presented in Table 6-7, which turns out to be very useful for the interpretation of the system. The baseline for comparison is the company's current data. The simulation shows that the most favorable scenario to avoid the incidence of occupational diseases, which leads to employees on leave, corresponds to the highest LoC. Although this level means a greater frequency of cycles (due to the reduced cycle time) and the performance of mental workload, the reduction in postural load seems to compensate for these factors.

Table 6-7. Comparison of sick leave and productivity for different LoC.

LoC	Sick Leave	Cycle Time
1	-5.6%	0%
2	-11.8	3.2%
3	-26.5	-6.9
4	-30.4%	-10.1%

Results demonstrate that inserting an industrial HRC system is complex. Both physical and mental workload may affect leave rate and productivity, which highly change the prospective scenarios.

6.4.4 Evaluation

6.4.4.1 Technical evaluation

Some critical checks were performed in order to verify if an industrial HRC system was technically practicable in the workstation with the mentioned characteristics. The main possibilities for a cobot to be useful are delivering, handling, and assembling. In this regard, the main complexities are those related to the work pieces: geometry, dimensions, loads, and materials; and, related to the organization: assembly location, layout, ranges, and sequences (Boothroyd, 2005). The critical technical issues follow the list presented in Gualtieri et al. (2020).

- Delivering: without perceived restrictions;
- Handling: three small components would be difficult for a cobot to manipulate;
- Assembly: some components are resistant to insertion, the assembly table is overconstrained, the assembly process demands reorientation of previous assembled components, and components must be compressed during assembly.

In summary, the small pieces must be manipulated by the worker and most of the assembly tasks require human skills to guarantee quality in the production line. Other tasks are considered feasible in terms of robot execution. For example, it is technically capable of handling and delivering the four larger pieces.

6.4.4.2 Ergonomic evaluation

An ergonomic intervention in the workstation by implementing an industrial HRC system will definitively change organizational, physical, and cognitive domains. In the new layout, work pieces must be delivered to the worker in a location closer to him, thus avoiding inappropriate postures on his part. By decreasing RULA scores, less WMSD is expected in the production line (Sharan & Ajeesh, 2012). On the other hand, mental workload also increases with repeatability of movements as psychological well-being depends on production flexibility (Shen & Reinhart, 2015).

The simulations showed the behavior of the system regarding the occurrence of sick leave and productivity for different LoC. Task subdivision increased worker's skills to accomplish the tasks and directly increased productivity. However, the influence of physical overload on output showed that productivity is also associated with stereotyped movement, which is often a consequence of repeatability or excessive task subdivision. Therefore, it is not recommended to overpush. Moreover, physiological recovery is needed in order to decrease the influence of physical overload on leave rate (Mattos et al., 2019).

In general, the inclusion of an industrial HRC system is beneficial for ergonomics. The main attention points are related to the new pace of work and the division of tasks between the worker and the cobot. These factors are better discussed in the economic evaluation.

6.4.4.3 Safety evaluation

Safety requirements: Due to the risk of collisions, a robot working without fences represent a risk in the HRC system (Santis, Siciliano, Luca & Bicchi, 2008). Safety management, sensors, and motion planning and control are the most important to avoid collisions (Gualtieri et al., 2021). According to ISO/TS 15066:2016 (ISO, 2016), the safety methods may vary for different LoC: safety-rated monitored stop, hand guiding, speed and separation monitoring, and power and force limiting.

Risk assessment: Similar assembly application with HRC evaluated as low risk for the human (Gervasi et al., 2020). However, an evaluation is important due to individual scenarios of a collaboration (Michalos et al., 2018). In this chapter, it has been considered that this evaluation does not change as the light-weighted pieces are delivered always at the same place by the robot, and safety requirements may follow robot's capabilities in different LoC, according to Table 6-3.

6.4.4.4 Economic evaluation

Considering the above mentioned regarding technical, ergonomic, and safety evaluations, an economic evaluation aims at recognizing the tasks for which a cobot provides value to the production process. As stated in Gualtieri et al. (2020), it is important to integrate organizational and economic factors for a better collaborative workstation.

Table 6-8 presents the division of the workstation tasks between human and cobot. In this case study, the assembly tasks must be performed by the worker, which means that all the value-added tasks were allocated to the worker. However, the cobot is capable of handling and delivering P1, P4, P5, and P6 (larger pieces), which means time saving in the production line. Moreover, according to the prospections of the model, less absenteeism is expected due to WMSD, which means maintaining human resources and knowledge.

Table 6-8. Division of the workstation tasks.

Component	Task	Human	Robot	Value Added	Time saving
P1	Delivering		X		+
	Handling		X		+
	Assembly	X		+	
P2	Delivering		X		+
	Handling	X			
	Assembly	X		+	
P3	Delivering		X		+
	Handling	X			
	Assembly	X		+	
P4	Delivering		X		+
	Handling		X		+
	Assembly	X		+	
P5	Delivering		X		+
	Handling		X		+
	Assembly	X		+	
P6	Delivering		X		+
	Handling		X		+
	Assembly	X		+	
P7	Delivering		X		+
	Handling	X			
	Assembly	X		+	

6.4.5 Decision

Considering the objectives, assessments, simulations, evaluations, and investments to be made, the workstation condition justifies the implementation of an industrial HRC system. It has been taken into account that by thinking about the whole system, higher levels of automation do not necessarily guarantee higher levels of productivity, safety, or operator well-being (Lagu & Landry, 2011). Higher LoC may induce other problems, such as confusion, complacency, or loss of certain skills. According to the classification suggested in Cohen et al. (2021), in order to achieve management expectations in short- and long-terms, a meaningful decision would be upon a cobot with capabilities in the Level 3 presented in Table 6-3.

Here are some final considerations. The new workstation must: ensure the cobot arm to reach the work pieces; consider workers anthropometric dimensions in the layout design; choose adequate technologies for gripping, safety, and recognition and awareness sensors.

6.5 Conclusion

Inserting a cobot into an assembly line is a complex decision. The dynamics of the elements that interact with each other can result in counter intuitive effects. In this context, decision-making needs to be carefully thought out and developed. The current framework addresses the challenge of implementing a cobot. Ergonomics, safety, and productivity were discussed based on system dynamics in a context of industrial assembly process. The system behavior and its prospective scenarios with HRC were key to managerial evaluation. Finally, a decision was made based on reliable data instead of a mental model, drastically reducing the risk of failure when deciding upon an HRC system. Therefore, this framework was presented to improve managerial decision assertiveness.

6.6 References

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CHAPTER 7 | Simulating Human-Robot Collaboration for improving ergonomics and productivity in assembly workstations: a case study

Abstract. Objective: To simulate the interaction human-robot regarding productivity, physical and mental workload, involving the worker in the process of implementing a new HRC system. Background: The guidelines for designing ergonomic and management of work systems are key to ensure worker safety, health, and wellbeing. It considers physical and mental workloads, including worker in the process of implementation. Method: Consists of comparing two workstations regarding physical demand, mental demand, and productivity with a sample size of 6 subjects. First workstation is a replica of a current situation, in which it is intended to implement an industrial HRC system. Second workstation is a human-robot simulated scenario, in which a human hand simulates the tasks being performed by a robot arm. Results: Robot-simulated scenario resulted in: 24.3% increase in productivity; posture exposure time reduced from 33.5% to 22.0%; overall workload felt by workers decreased from 44/100 to 38/100; and participatory ergonomics provided meaningful insights for better understanding the whole system. Conclusion: Robot-simulated improved ergonomic conditions and productivity compared to the replica-workstation and it is important to involve the worker in the implementation of an HRC system. Application: Assembly task workstations considering the inclusion of an industrial collaborative robot to perform tasks and lighten the burden on humans.

7.1 Introduction

Machines have been introduced to industrial environments in order to improve productivity, quality, cost, and ergonomics (Gualtieri et al., 2020). Recently these interactions between human and machines advanced to collaborative robots (cobots) that allows human to work alongside them without barriers, aimed at achieving a common goal (Gervasi et al., 2020). According to IEA & ILO (2020), there are six guidelines for designing ergonomics and management of work systems to ensure worker safety, health, and wellbeing. These guidelines should be adapted to each situation, especially when emerging new technologies and new forms of work. First, ergonomics has to be seen as a system. Both physical and cognitive domains are equally important, as workers' capabilities and limitations prevail when designing a workplace. It can be accomplished by giving appropriate tools, training, and continuous learning, as well as by not allowing the robots or machines dictate matters. Participatory ergonomics is also relevant as experienced workers in a task have many ideas of how to improve the workplace, and also because workers need to know the system they are working in. Finally, the design of a work system has to be safe, healthy, promote wellbeing, and be sustainable. Figure 7-1 shows the main guidelines:

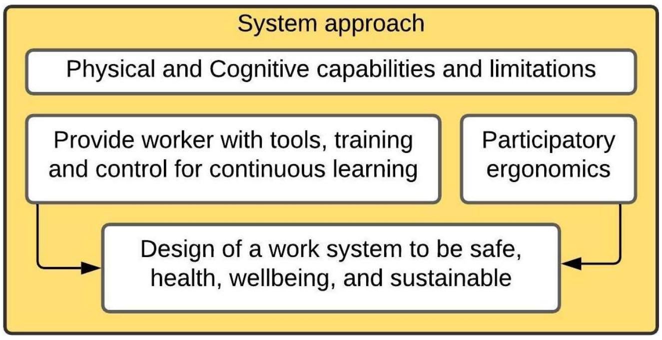

Figure 7-1. Guidelines for ergonomic design and management in work systems.
Source: Adapted from IEA & ILO (2020).

The design and implementation of HRC systems are complex. As stated by Charalambous et al. (2015) and Charalambous, Fletcher, & Webb (2016a), to ensure acceptance and for a successful implementation of an industrial HRC system, it is crucial to understand the ergonomics (physical, cognitive, and organizational). Several studies consider the three dimensions, for example, in Ender et al. (2019) where the design aims at optimizing workplaces for manual production and maintenance processes; and in Changizi, Dianatfar, & Lanz (2019), where the concept design considers human mental and physical viewpoints at the same time by proposing a hand-guiding on the robot in order to make the workers fell having control over the system, with the robot as a helper instead of a robot giving an object.

However, it is not easy to quantify the benefits in terms of ergonomics and productivity, at the same time that considers the guidelines above mentioned. Therefore, this chapter aims at simulating the interaction human-robot regarding productivity, physical and mental workload, as well as involving the worker in the process of implementing a new HRC system.

7.2 Materials and Methods

The workstation selected for this study is a manual assembly of seven work pieces (P1 to P7). The method consists of comparing two situations regarding physical demand, mental demand, and productivity with 6 workers. A replica-workstation (Figure 7-2a) was built maintaining the same dimensions as the real workstation, imposing on the worker the same postures to reach the components to be assembled. While the robot-simulated scenario is presented in Figure 7-2b, in which a human hand works simulating a robot arm to deliver the four largest components (P1, P4, P5, and P6), one at a time, and the remaining three components are placed next to the worker (P2, P3, and P7). Under this study the assembly table remains at the same place regardless the scenario.

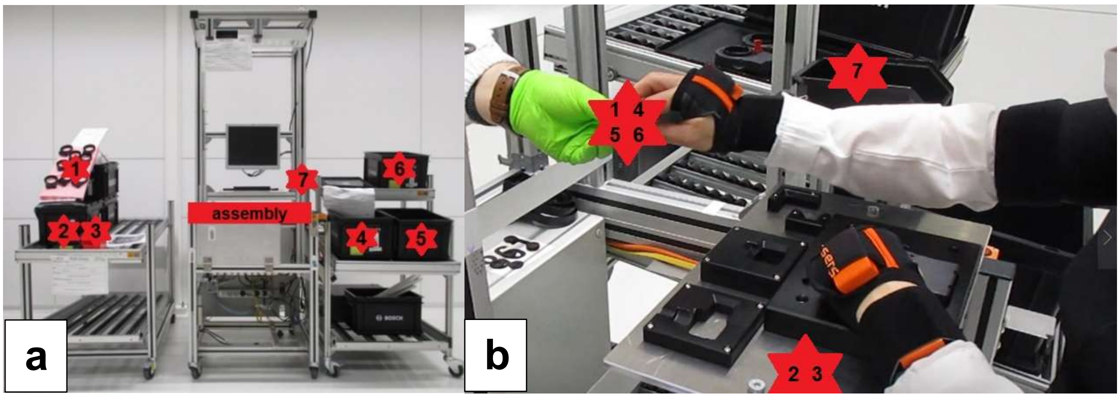

Figure 7-2. Simulation scenarios: a. Replica-workstation; b. Robot-simulated.

7.2.1 Productivity

Cycle time is the variable chosen to measure productivity. Workers were asked to perform twenty minutes of task execution, in which the cycle times were measured by using a digital stopwatch. They were not allowed to stop working during this period of time. However, in both scenarios the pace was dictated by each worker, according to their individual abilities and motivation.

7.2.2 Physical Demand

Workers were chosen by gender and classes of percentiles in order to obtain data from a larger range following the anthropometric database for Portuguese adult workers (Barroso et al., 2005). For this study it means one woman and one man in between the percentiles 5-35, 35-65 and 65-95 using stature as the dimension of reference (Qutubuddin, Hebbal, & Kumar, 2012). The motions were captured during six cycle times by using Xsens MVN software, in which the Xsens' RULA algorithm was applied. The output is a percentage of time the worker was under each of the four risk levels (negligible, low, medium, high).

7.2.3 Mental Demand

The ergonomic method NASA-TLX (Hart & Staveland, 1988) was applied after workers performed the task. This questionnaire is divided in two parts:

First, workers choose on a scale of 21 graduations, their own perception of the task.

- Mental Demand - How mentally demanding was the task? (Thinking, deciding, calculating, remembering, looking, searching);
- Physical Demand - How physically demanding was the task? (Pushing, pulling, turning, controlling, activating) Was the task easy and restful or demanding and laborious?
- Temporal Demand - How hurried or rushed was the pace of the task? Was the task slowly and leisurely or rapid and frantic?
- Performance - How successful were you in accomplishing what you were asked to do? How satisfied were you with your performance?
- Effort - How hard did you have to work to accomplish your level of performance?
- Frustration - How frustrated were you during the task? Were you insecure, discouraged, irritated, stressed, and annoyed or secure, gratified, content, relaxed and complacent?

Second, they were asked to choose between two items (fifteen pairs) which one represents the more important contributor to the workload for the task performed. The rating of the first part combined with the weight of the second part gives the overall workload of the task for an individual.

7.3 Results

Productivity was measured during 20 minutes of the assembly task. The average cycle time in the replica-workstation was 23.10s and in the robot-simulated 18.59s (-19.5% Cycle Time) which means a 24.3% increase in productivity. The standard deviation in the robot-simulated is lower, in general, which is beneficial in terms of production line stocks. The results are presented in Table 7-1.

Table 7-1. Cycle time for replica-workstation and robot-simulated scenarios.

	Worker 1		Worker 2		Worker 3		Worker 4		Worker 5		Worker 6	
	RW	RS	RW	RS	RW	RS	RW	RS	RW	RS	RW	RS
Cycle Time (s)	23.02	18.15	21.46	17.87	24.68	16.81	29.63	25.96	22.11	17.54	17.71	15.23
Standard Deviation (s)	1.78	1.68	1.22	1.61	2.23	1.56	2.87	2.39	1.47	1.33	1.52	1.53

RW – Replica-workstation; RS – Robot-simulated.

Physical demand was evaluated through RULA risks calculated by Xsens in percentage time of exposure to medium and high risks. The medium and high risks are presented in Figure 7-3 for each percentile in both replica-workstation and robot-simulated scenarios. It shows that exposure decreases in all cases, as in the robot-simulated the workers' movements are less painful. Especially smaller workers (percentile 5-35) felt the benefits of reducing their exposure time from 27.0% (medium risk) + 6.5% (high risk) to 21.5% (medium risk) + 0.5% (high risk).

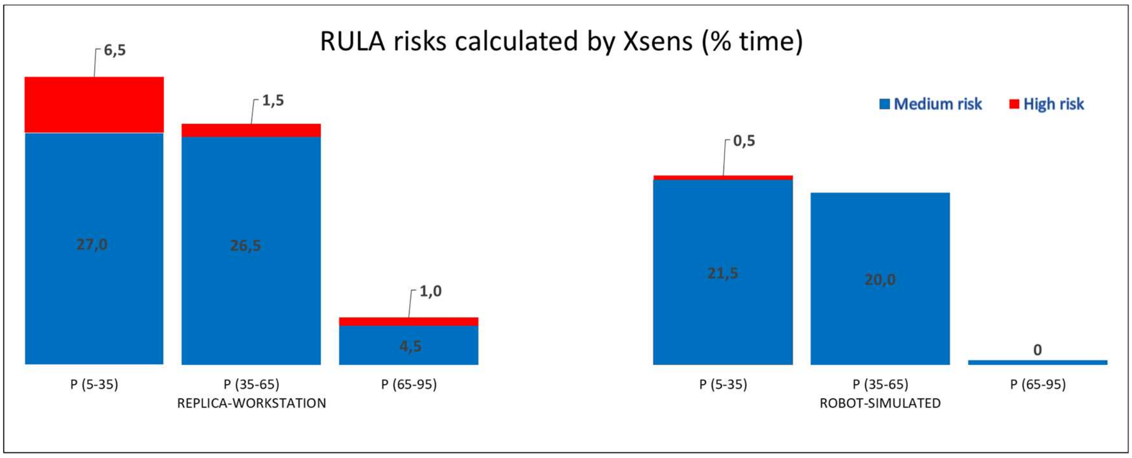

Figure 7-3. RULA calculated by Xsens in percentage time of exposure in replica-workstation and robot-simulated scenarios for different percentiles.

Figure 7-4 shows that implementing a helper to deliver work pieces decreased the overall workload felt by workers from 44 to 38. However, temporal demand, performance and frustration results indicate that workers felt more uncomfortable performing the task even having control over the pace of work.

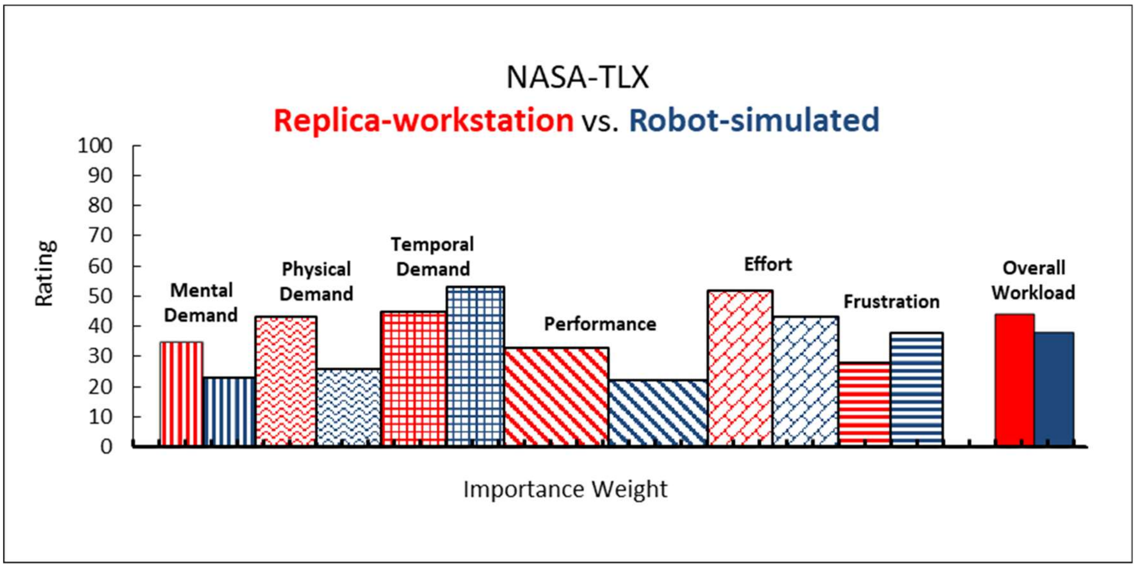

Figure 7-4. NASA-TLX ratings and overall workload for replica-workstation and robot-simulated scenarios.

In summary, the results corroborate with Turk, Resman, & Herakovič (2021), in which the redesign of an assembly workstation improved ergonomics and productivity time and errors.

7.4 Discussion

This case study compared two workstations regarding ergonomics and productivity, by involving six workers from different anthropometric percentiles, genders, and letting them work on their own preferences. This is according to Stoehr, Schneider, & Henkel (2018), which pointed that work instructions should be individualized and user oriented, involving each user no matter limitations or disabilities. Otherwise, as stated by Green, Billinghurst, Chen, & Chase (2008), by not reasoning ergonomics, the HRC system may present undesired effects, such as fatigue, monotony, and performance decrements. Regarding posture, Sanders & McCormick (1987) advise that the workstation should provide several working positions since there is no ideal posture that can be selected for the long term. Therefore, the most efficient work position during an assembly task with a robot, which requires a continuing operation, is the worker choose between standing and sitting positions. In this study only the standing position was considered in order to replicate the original workstation and make them comparable. Also, the percentiles chosen related to static dimensions and, according to Changizi et al. (2019), standard anthropometric data only present information about static or fundamental features in usual postures. In summary, risky postures and overall physical workload were reduced by including a helper delivering components in front of the worker, which is expected to follow the same pattern with an industrial HRC system.

Regarding the cognitive aspect, Ogorodnikova (2008) proposed a framework that highlights workforce training and empowerment as cognitive important features when planning and designing an HRC workplace. In order to emphasize this topic, Busch, Toussaint, & Lopes (2018) said that optimizing simultaneously task allocation while taking into account ergonomic aspects improves acceptance. In this research the work pieces were arranged to optimize both robot and human tasks. Results showed that mental demand was reduced, however, other psychological factors increased. This aspect should be considered more seriously when planning the robot motion control, as advised in Sadrfaridpour, Saeidi, Burke, Burke, Madathil, & Wang (2016). Instead of NASA-TLX, a possible cognitive assessment might be useful in the presence of a robot by applying the Trust Scale Questionnaire presented in Charalambous, Fletcher, & Webb (2016b).

Productivity increased as a consequence of having a teammate performing the task. In this regard, considering human and robot as teammates in HRC systems, an interesting comparison was done by Lindblom & Wang (2018): "To keep track of the environment the robot uses cameras and sensors, when humans use several senses; to safeguard the human the robot is equipped with artificial intelligence, as well as the worker must have knowledge of the robots, human-robot interactions and the assembly process."

Finally, in order to decide which level of collaboration to implement, considering the cobot capabilities suggestions in Cohen, Shoval, Faccio, & Minto (2021), and the results obtained in this study, the competence Level 3 is adequate. It means the cobot: gets information from sensors and cameras; follows the preprogrammed schedule to move between stations; is responsive to human gestures and speech; and brings tools next to the operator.

By involving the operator in the process, it was possible to identify improvements when implementing the HRC system:

- A robot is only capable of delivering work pieces as in the case study, not assembling pieces itself due to restricted space.
- Even with the pace of work given to the human, psychological aspects still need to be better addressed.
- The assembly table could be lower in order to balance the physical demand of the three defined percentiles in the robot-simulated scenario.
- A sitting position is an option to be considered in such workstations, probably with adjustable assembly table height.

It would be more precise to consider ranges in defining percentiles, instead of static anthropometric dimensions.

7.5 Conclusion

As a conclusion, it has been noticed an improvement in ergonomic conditions by using a robot-simulated compared to the replica-workstation. Xsens showed that postures were improved, NASA-TLX showed a decreased in the overall workload perceived, and productivity increased 24% on average when compared to the workstation without aid. Moreover, involving the worker in the process was key to understand important features to be considered when including a real robot.

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CHAPTER 8 | Discussion

The main findings of the thesis are divided into two research topics: a system dynamics model for HRC workplaces and decision-making framework for implementing HRC systems. In order to discuss the theoretical and practical implications of the work, the related literature is included to contextualize the advances in these fields.

8.1 System dynamics model

The safety of the operator is a priority in HRC systems due to the removal of barriers, in which the risks of collision increase in higher LoC. Therefore, information about the environment is crucial to be detected and controlled (Bdiwi et al., 2017). Some variables to reduce the damage of a potential accident are: to reduce weight, speed and accelerations (energy in motion); to vary power transmission during tasks (inertia); to plan robot's movements and trajectories to look natural for an human being; and to avoid lack of visibility (Santis et al., 2008). The interaction and communication can be achieved with the design of the mechanism, sensors, actuators, and system architecture.

According to Robla-Gomez et al. (2017), the techniques for localization and safety in HRC workplaces can be achieved with: Geometrical representation of the environment using numerical algorithms; Inertial motion capture system using four fixed camera sensors; Local information capture using sensors; Artificial intelligence using cameras; and Kinect sensor using machine learning to recognize human hand gestures in real time. Robots must be equipped with sensors and cameras to react and ensure safety in case of unexpected human's movements.

For HRC being efficient it is important that robots understand human gestures correctly and act based on this information. According to Liu & Wang (2018), the five phases in HRC gesture recognition are: data collection, gesture identification, gesture tracking, gesture classification, and gesture mapping. First, gestures are captured through sensors (cameras, depth sensor, wearables, or radio frequency). Once the robot captures human gestures, they are classified to drive the physical response of the robot, which is one of the main phases in HRC system performance. Depending on the sensor used to capture, the gesture identification can be made by visual devices, machine learning algorithms or skeleton models, which can be classified based on different machine learning algorithms. Literature conclusions on this topic suggests that either skeleton model (gesture identification) together with depth sensor (gesture recognition) or radio frequency (gesture identification) together with deep learning (gesture recognition) are very promising technologies to monitor human movements. However, these technologies still need higher quality and faster responses do guarantee safety of human workers in HRC systems.

In order to have real-time responses, wearable technologies together with machine learning algorithms are an option. For instance, CyberGlove® can measures the wrist, hand, finger movements and grip pressure during work, while Xsens® can capture whole body motion using inertial sensors. Xsens® is also capable of a real time ergonomic assessment during tasks, which was used to score RULA in the case study of this thesis. However, wearable technologies are still not comfortable to wear on a regular basis. According to Ramasubramanian, Aiman, & Papakostas (2021), "Inertial Measurement Units and vision sensors are expected to be the workhorses in operator tracking applications. The increase of computing power, the further improvement of the performance of machine learning approaches, the Industrial Internet of Things and Industry 4.0 technologies will all contribute to the faster integration of sensors in standard production environments. However, the data accuracy, the data analysis speed, implementation and maintenance costs, together with ethics and General Data Protection Regulation issues will be the most critical factors that will affect when and how wearable devices will be massively introduced and integrated into HRC applications. At the same time, it is important to note that sensor-based human operator tracking HRC tasks will have to offer advantages that surpass the implementation costs". Taken it into account, from the ergonomic and safety point of view, there is no ideal solution for preventing accidents in HRC systems. Unfortunately, it is still necessary to deal with the complexity of accidents and its causes.

As already presented in Chapter 2, there are many models to address accidents in the industry as shown in Table 8-1. SD is an option to overcome some of the limitations found in other models.

Table 8-1. Models to address accidents in industry.

	Sequential	Risk Analysis	Simulation
Models often used in industry	HAZOP FTA FMEA/FMECA	RMF HFACS FRAM STAMP	DES ABM
System Dynamics	Cause-effect feedback, interaction between variables, behaviors within a system, support decision-making, applied both retrospectively to accident analysis and predictively to risk assessment, and model uncertainty.		

In summary, human safety in HRC systems may be addressed by several technologies. The non-wearable are the most promising, however, only wearable technologies guarantee a fast response to movements. The problem is that, in a practical workstation, wearables go against ergonomics in many ways. Therefore, it is not possible to rely on these solutions and it is still necessary to look at the whole system to design a safer workplace. The more often models to address accidents in industry either do not consider the interactions among system factors or lack providing support for decision-making.

The procedures to develop SD models are well grounded in the literature and the tools are consolidated to generate useful qualitative and quantitative information. There are SD models focusing in each aspect of the current problem: dynamics of a production line (Sterman, 2000); system safety (Shire, Jun, & Robinson, 2018); ergonomic assessment (Abaeian et al., 2016); knowledge and physical workload on assembly performance (Mattos et al., 2019); mental workload (Jafari et al., 2019) and evaluation of psychosocial risk factors (Abaeian et al., 2017); effects of injury risks on productivity and quality (Farid & Neumann, 2019); costs for implementing robots in general (Elizondo-Noriega, Tiruvengadam, Güemes-Castorena, Tercero-Gómez, & Beruvides, 2019); and policies on occupational health and safety (Bastan, Baraftabi, Groesser, & Sheikhahmadi, 2018).

Sterman (2004) mention that a broad model boundary that captures important feedbacks is more important than a lot of detail in the specification of individual components. Therefore, a model was built to represent the cycle of production self-regulation (cause and effect that adjust the work pace to meet production goals), the cycle of learning by repetition (experience and knowledge that leads to greater skill to execute a task), the cycle of limitation due to disease incidence (consequences of WMSD caused by human overload), and the cycles of physical and mental workloads, which are the primarily responsible for causing sick leave, reduction of task knowledge, increases in cycle time, and finally making it more difficult to meet production goals (reinforcement cycle).

The main advance of the SD simulation model presented in this work is that it completely represents an industrial HRC system. It considers ergonomics (physical and mental workloads), productivity and LoC, which together are a combination of decisive factors when deciding which robotic system to implement. Moreover, as pointed by Dulac & Leveson (2004), although decisions may seem safe and reasonable locally in the individual work environment, they may interact in unexpected ways considering the entire system operation. Some variables could be further explored, such as individual characteristics (medical history, age, working time, gender) for the model to represent a more personalized reality. The inclusion of a workforce subsystem would also be helpful in increasing understanding of worker performance.

8.2 Decision-making framework

Ergonomics and productivity are the two main targets for implementing an industrial HRC system (Kim et al., 2019). By assessing both physical and mental workloads it is expected best results in terms of WMSD prevention, once they complement each other to understand sick leaves in industrial environments. In general, when choosing ergonomic methods, it is also interesting to consider different perspectives in order to avoid addiction. Therefore, complementary approaches take into account that applying questionnaires, check the employee perceptions, observational methods add a professional view over the workstation, and the direct methods measure specific activities.

Physical fatigue is a transient inability of muscles to maintain a load, a decrease in the maximal force that the involved muscles can produce and develops due to sustained physical activity (Enoka & Duchateau, 2008). When the workers are exposed to WMSD risk factors they begin to fatigue (Mukhtad et al., 2018). Similarly, mental fatigue is a transient decrease in maximal cognitive performance resulting from prolonged periods of cognitive activity (Marcora et al., 2009). Psychosocial and organizational factors may lead to stress, anxiety, and fatigue, which increase the risk of WMSD (EU-OSHA, 2020). The relationship is so close that Davis, Marras, Heaney, Waters, & Gupta (2002) affirm cognitive disorders increase the biomechanical response of the musculoskeletal system to physical factors, which may enhance the risk of WMSD. As pointed by Wilson (2014), leading ergonomists have seen that the cognitive interactions are intimately related to the physical ones, and it is necessary to address WMSD at a systems level.

In summary, a framework for implementing an industrial HRC system should consider all ergonomic domains. It is useful to apply a screening tool for organizational understanding, in which EWA/FIOH has been often chosen. There are many methods to assess physical workload in manual assembly tasks. The most used are RULA, OCRA, EAWS, NIOSH, KIM-MHO, NMQ, and EMG. To assess mental workload, it is more common to choose between NASA-TLX and EDA. It is possible to combine them to draw a conclusion on the global risk of a specific task, as each method has its advantages and limitations.

In the case study presented in this work, RULA method has been chosen as the ergonomic method to assess the physical workload. RULA scores were automatically calculated by the algorithms contained in the software Xsens® as WMSD may result from a high rate of repetitive work with a short cycle time and lightweight tool (Bjoering & Haegg, 2000). Mental workload, which is one of the risk factors associated with the incidence of WMSD (Fadaei, Habibi, & Hasanzadeh, 2020) and often neglected in empirical studies as presented in the conclusions of Chapter 3, was estimated by applying the NASA-TLX questionnaire.

On the other hand, productivity makes investments possible in the industry. Acquiring a lightweight robot to work as a teammate deserves the attention of the financial department. A manager who proposes such an investment must present reasonable justification. In this regard, increase production and cycle time are often used to measure productivity (Elizondo-Noriega et al., 2019; Mattos et al., 2019). Moreover, the investment amount depends on the technology chosen. Advanced capabilities of a cobot (higher LoC) means more technology, mobility, costs, often more productivity, less physical effort, and everything must be taken into account when deciding beforehand by management. The whole system evolves differently depending on management choices. Therefore, a computational model is key to understand the complexity of HRC workplaces, to prospect scenarios and to predict the system's behavior.

All that information is essential when inserting a collaborative robot into an assembly line. A decision in this regard is complex and a framework is called for implementing a collaborative robot. Chapter 6 presented a framework based on system dynamics that consider the three ergonomic domains, productivity, and different LoC in a context of industrial assembly process as input for decision-making. Moreover, prospected scenarios can predict the system's behavior, which together with technical and economic evaluations are the fundamental for managerial evaluation. Therefore, management considerations are made based on reliable data, increasing assertiveness in decision-making.

The literature shows in Table 8-2 frameworks, simulations, and methods for designing and implementing industrial HRC systems. From this list, it can be noticed that there was no framework using SD in HRC.

Table 8-2. Frameworks, simulations and methods for designing and implementing industrial HRC systems.

HRC design and implementation	System approach		Ergonomics			Productivity / Performance	LoC
	SD	Other	Org	PW	MW		
Thesis' Framework	x		x	x	x	x	x
(Nicora, M. L., Ambrosetti, R., Wiens, G. J., & Fassi, 2021)						x	x
(Kopp, Baumgartner, & Kinkel, 2020)		x	x		x	x	
(Colim et al., 2020)			x	x		x	
(Gualtieri, Rojas, Garcia, Rauch, & Vidoni, 2020)			x	x		x	
(Changizi et al., 2019)				x	x		
(Lauer, T., Welsch, R., Abbas, S. R., & Henke, 2020)		x				x	x
(Kim et al., 2019)		x	x	x		x	x
(Maurice, Padois, Measson, & Bidaud, 2019)		x		x			x
(Petruck, Nelles, et al., 2019)			x	x		x	
(Vazquez & Jabi, 2019)		x	x	x	x	x	
(Pearce, Mutlu, Shah, & Radwin, 2018)			x	x		x	x
(Heydaryan, Bedolla, & Belingardi, 2018)		x	x	x		x	
(Petruck & Mertens, 2018)		x			x	x	
(Eichler, Winkler, & Bdiwi, 2018)			x	x		x	
(Kim, Lee, Peternel, Tsagarakis, & Ajoudani, 2017)		x		x			
(Malik & Bilberg, 2017)		x				x	
(Charalambous, Fletcher, & Webb, 2017)		x	x		x		
(Koppenborg et al., 2017)		x	x	x	x	x	
(Sadrfaridpour, Saeidi, & Wang, 2016)			x	x	x	x	
(Pini et al., 2016)			x	x		x	
(Djuric, Rickli, & Urbanic, 2016)		x				x	
(Sadrfaridpour, Saeidi, Burke, et al., 2016)		x	x		x	x	

SD – System Dynamics; Org – Organizational; PW – Physical Workload; MW – Mental Workload; LoC – Level of Collaboration.

In summary, a system view which integrates ergonomics, performance, and different scenarios regarding the LoC of an HRC solution is key managerial decision-making. The framework presented in this work can be used in similar situations, as it brings basic aspects to consider when redesigning a system. This approach corroborates with authors conclusion that SD models increases the knowledge of how ergonomic risk can develop while performing tasks (Abaeian et al., 2016), which are important to prevent WMSD (Lorenzini et al., 2019).

8.3 Major Contributions

In order to answer the research question: "How to reduce uncertainty in decision-making for ergonomic interventions?"

Making good decisions in ergonomic interventions is very much related to:

- Look at the whole system, the most important factors and its interconnections;
- Acquire reliable data using ergonomic methods;
- Prospect scenarios with the aid of a computational simulation model;
- Follow a structured procedure for decision-making processes.

Therefore, this work contributes to the literature by building on the knowledge of SD modeling with the inclusion of an industrial HRC system, and by presenting a framework to increase assertiveness in decision-making when implementing cobots.

8.4 Limitations

This work was developed in the context of a research project in a collaboration between the University of Minho and the company Bosch Car Multimedia Portugal. During the project period there were many restrictions due to the Covid-19 pandemic. This means that it was not possible to carry out the case study with more people and that the research could not advance further due to the lack of a collaborative robot available. These questions forced the adequacy of the research strategy and scope.

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CHAPTER 9 | Conclusions and Future Work

This thesis addresses the complexity of WMSD in the industry. It has dealt with prospected scenarios of productivity, mental and physical workloads when implementing an industrial HRC system, as such understanding on system's behavior for different LoC is key for managers to make good decisions.

In general terms, the conclusions can be synthesized in three main points.

First, this work concluded that managers are more likely to make better decisions based on a model which presents qualitative and quantitative results of prospected scenarios than based on mental models' expectations.

Second, analysis of the prospected scenarios concluded that counterintuitive effects might appear, as higher LoC do not guarantee higher levels of productivity and safety. The model presented is useful to predict the best working conditions between human and robot. Moreover, the framework included technical and economic evaluations as the basis for managerial decision upon an HRC system. The case study concluded that the risk of failure in decision-making was drastically reduced and, in that case, the cobot's competence Level 3 was chosen.

Third, an actual experiment was carried out to compare productivity, physical and mental workloads in two situations: a replica-workstation and a human-robot scenario. The conclusion was that ergonomic conditions improved (postures and overall workload) and productivity increased 24% on average with the robot-simulated. Real simulations results corroborate with computational simulations and indicate that competence Level 3 meets the requirements in terms of ergonomics and productivity.

Finally, the main objective of the thesis, which was to reduce the risk of WMSD by developing a decision-making framework for implementation of HRC systems, was achieved by developing a computational model to represent the HRC system's behavior, and by prospecting scenarios of ergonomics and productivity for different LoC. Moreover, these outputs are integrated into a framework, in which technical and economic evaluations are also taken into account, for making decisions that are feasible and reduce the risk of WMSD in ergonomic interventions.

Future work

This work developed two main topics: an SD model for HRC workplaces and a framework for decision-making when implementing a cobot. Based on these advances, it would be interesting to further investigate the following aspects:

- To model focusing on finances (e.g., income, costs) in HRC systems for different LoC;
- To explore the practical application of this framework in other assembly lines that consider the insertion of an HRC system;
- To apply a trust questionnaire in a collaborative workstation, comparing the results with those obtained by the application of the NASA-TLX questionnaire.

Appendix

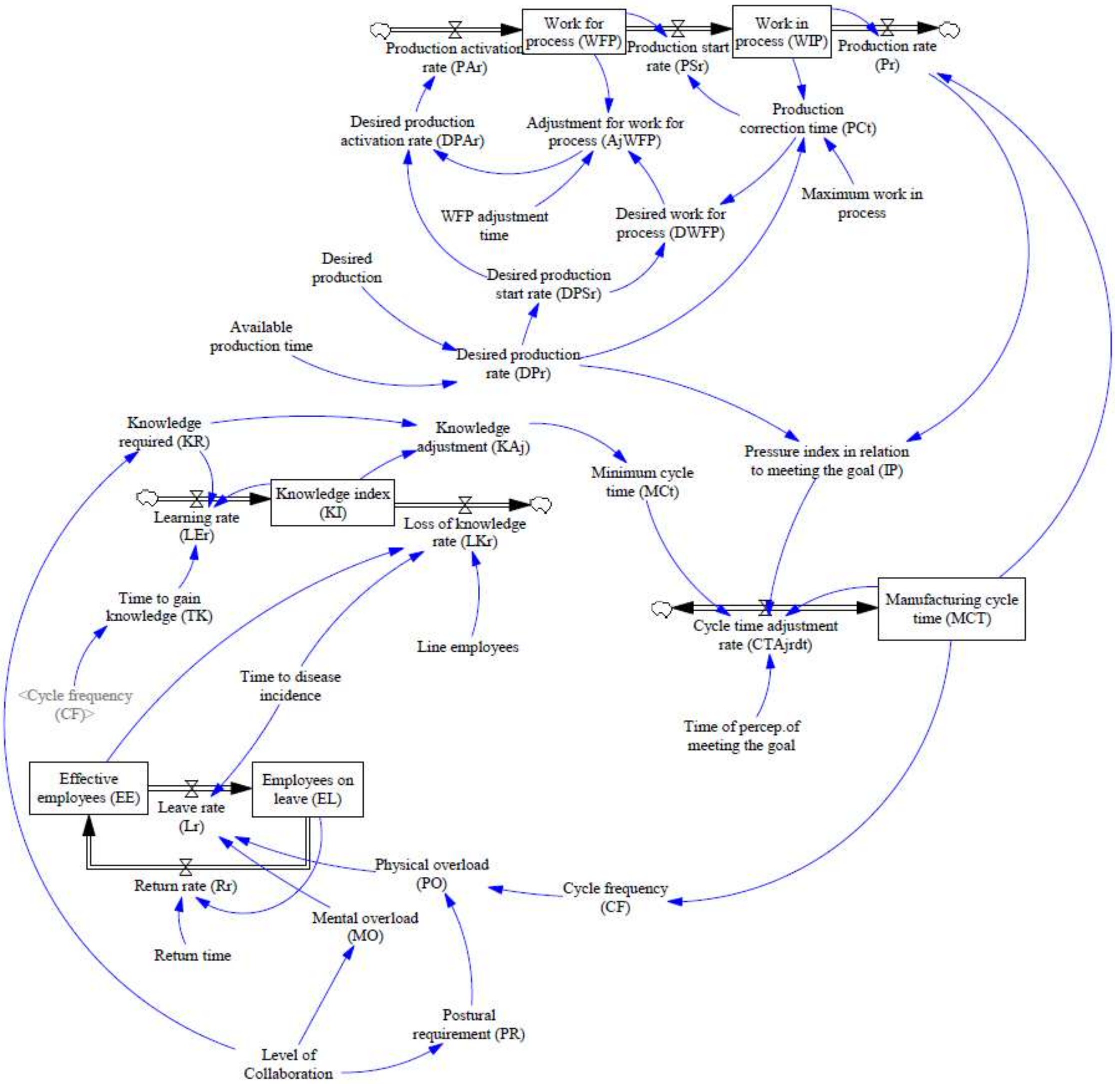

Figure A.1. Stock and Flow Map.

Table A.1. Model equations.

Label	Equation	Unit
Work for process (WFP)	$WFP = \int_{t_0}^{t} [PAr - PSr]dt + WFP_{t_0}$	Tangible goods
Work in process (WIP)	$WIP = \int_{t_0}^{t} [PSr - Pr]dt + WIP_{t_0}$	Tangible goods
Production rate (Pr)	$Pr = \frac{WIP}{MCT}$	Tangible goods/Week
Production start rate (PSr)	$PSr = \frac{WFP}{\mathrm{PCt}}$	Tangible goods/Week
Desired production start rate (DPSr)	$DPSr = \mathrm{DPr}$	Tangible goods/Week

Table A.1 - Model equations (continuation).

Adjustment for work for process (AjWFP)	$\text{AjWIP} = \frac{(\text{DWFP} - WFP)}{WFP\ adjustment\ time}$	Tangible goods/Week
Desired work for process (DWFP)	$\text{DWIP} = \text{PSr} \cdot \text{PCt}$	Tangible goods
Desired production rate (DPr)	$\text{DPr} = \frac{\text{Available production time}}{\text{Desired production}}$	Tangible goods/Week
Manufacturing cycle time (MCT)	$\text{MCT} = \int_{t_0}^{t} (CTAjrdt) + WFP_{t_0}$	Week
Production activation rate (PAr)	$\text{PAr} = \text{DPAr}$	Tangible goods/Week
Production correction time (PCt)	$\text{PCt} = \frac{\text{Maximum work in process} - \text{WIP}}{\text{DPr}}$	Week
Cycle time adjustment rate (CTAjrdt)	$\text{CTAjrdt} = \frac{\text{MiCt} - \text{MCT}}{\text{Time of percep. of meeting the goal} \cdot IP}$	
Desired production activation rate (DPAr)	$\text{DPAr} = \text{AjWFP} + \text{DPSr}$	Tangible goods/Week
Pressure index in relation to meeting the goal (IP)	$\text{IP} = \frac{\text{DPr}}{\text{Pr}}$	
Minimum cycle time (MiCt)	$\text{MiCt} = \text{f (KAj)}$	Week
Knowledge adjustment (KAj)	$\text{KAj} = \frac{\text{KI}}{\text{KR}}$	
Cycle frequency (CF)	$\text{CF} = \frac{1}{\text{MCT}}$	Cycles
Postural requirement (PR)	$\text{PR} = \text{f (Level of Collaboration)}$	
Mental overload (MO)	$\text{MO} = \text{f (Level of Collaboration)}$	
Physical overload (PO)	$\text{PO} = \text{f (Level of Collaboration)}$	
Knowledge required (KR)	$\text{KR} = \text{f (Level of Collaboration)}$	Knowledge
Effective employees (EE)	$\text{EE} = \int_{t_0}^{t} [\text{Rr} - \text{Lr}]dt + \text{EE}_{t_0}$	Employees
Return rate (Rr)	$\text{Rr} = \frac{\text{EL}}{\text{Return time}}$	Employees/Week
Leave rate (Lr)	$\text{Lr} = \frac{\text{MO}}{\text{Time to disease incidence}}$	Employees/Week
Employees on leave (EL)	$\text{EL} = \int_{t_0}^{t} [\text{Lr} - \text{Rr}]dt + \text{EL}_{t_0}$	Employees
Time to gain knowledge (TK)	$\text{TK} = \frac{480}{\text{CF}}$	Week
Knowledge index (KI)	$\text{KI} = \int_{t_0}^{t} [\text{LEr} - \text{LKr}]dt + \text{KI}_{t_0}$	
Learning rate (LEr)	$\text{LEr} = \frac{\text{KR} - \text{KI}}{\text{TK}}$	Knowledge/Week
Loss of knowledge rate (LKr)	$\text{LKr} = \frac{\text{EE} - \text{Line employees}}{\text{Time to disease incidence}}$	Knowledge/Week