AN ABSTRACT OF THE DISSERTATION OF

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Abstract approved:

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David A. Nembhard

Teamwork has become a popular operational strategy applied as part of workforce management plans in manufacturing and service industries. Teamwork has been commonly used in organizations to pursue different goals such as increase business operations agility, boost company productivity, improve quality in operations, increase company flexibility, promote collaborative learning, hasten the learning process of novice workers during training, promote employee's motivation, or in some cases as a necessary tool to perform specific operations that cannot be performed by individual workers. Previous work has shown that the application of a teamwork strategy as part of the organization workforce management plan can positively impact the organization outcomes via creativity, innovation, motivation and learning. However, there is also evidence that a teamwork strategy can have a significant negative impact on organizational outcomes if the strategy is not properly designed and implemented because of greater demands on cooperation, limitations in communication, conflicts among workers, and cognitive biases. The impact of the benefits and relative costs of teamwork as part of workforce management plans are mostly determined by the design and implementation of a teamwork strategy and by the specific task and organization in which the teamwork strategy is applied. Thus, the informed design of a teamwork

strategy is necessary in order to obtain the maximum benefit of its implementation in organizations.

The literature on teamwork has mainly focused on observational studies that facilitates the understanding of teamwork dynamics based on team composition and how these affect individuals and team performance. However, the translation of findings in these studies to operation research strategies for workforce management application has been limited. Specifically, studies that address workforce allocation when is applied a teamwork-based strategy implementation in organizations has received little attention in literature, while the consideration of team dynamics from both perspectives, gains and losses, simultaneously is still a gap in the literature of operation research for the study and development of workforce management plans.

The goal of this dissertation is to reduce this gap, addressing the design of workforce management plans that considers the implementation of a teamwork strategy accounting for the gains and losses that arise from team dynamics. This work presents the exploration of the team formation process from the perspective of team size for learning-productivity environments. Workforce heterogeneity is considered through the modeling of individuals' productivity as function of individual learning parameters. Team dynamics are incorporated in an individual productivity model by including learning by knowledge transfer, which accounts for the benefits in individual productivity that can be gain though the interaction of workers within the team, and by including process loss, which accounts for the losses in individual productivity that arise from demand in coordination, conflicts, motivation losses and communication challenges that arise in teams. The methodology used in the study centers on the use of simulation and explicit mathematical representations based on models in the literature.

This dissertation 1) explores the jointly effects of human and organizational factors on system performance and their relevance to the worker-cell assignment problem, which demonstrates the value of considering these factors as part of the workforce planning process in a cellular manufacturing setting; 2) investigate the joint effects of knowledge transfer and the process loss on team performance resulting from the incorporation of additional workers into the work team and its implication on the optimal team size when considering different type of task structures; and 3) explores the team formation problem with the aim of characterizing optimal team size in a multiple work-team setting. This dissertation will serve as basis for the development of mathematical models to address the team formation problem as part of operation research applications considering individuals productivity gain and losses which results from team dynamic and provide insight to guide managers in making decisions about team design and teamwork strategy implementation.

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The Team Size Paradox: Knowledge Transfer and Process Loss Effects on Team Formation

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Yaileen M. Méndez-Vázquez

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CHAPTER 1

Introduction

1.1 Motivation

Teamwork has been a commonly applied strategy across different organizational settings, such as military service (Boies & Howell 2016), healthcare (Schultz & Melson 1990; Creaghead 2002; Househ & Lau 2005; Reagans et al. 2005; Manukyan et al. 2013; Ervin et al. 2018), project management (Schneider 1995; Lewis 1998; Huckman et al. 2009; Wi et al. 2009; Gutiérrez et al. 2016), and academic institutions (Ehrlenspiel et al. 1997; Drach-Zahavy & Somech 2002; Olalekan & Ayinla 2014), with the aim of improving the performance of the organization, hastening the learning process of individuals within the organization, and achieving levels of performance and system flexibility that could not be attained with an individual work strategy (Cohen & Levesque 1991; Bursic 1992; Hamilton et al. 2003; Reagans et al. 2005; Ogungbamila et al. 2010; Olalekan & Ayinla 2014; Ervin et al. 2018; Jin et al. 2018). Although numerous benefits have been highlighted in previous studies related to the implementation of teamwork, several challenges have also been identified that arise from the implementation of this organizational strategy.

Some of the identified benefits include workload division, learning from knowledge transfer, increase in collaboration, amplification of individual perspective, and incrementation of organizational expertise (Drach-Zahavy & Somech 2002; Baeten & Simons 2014). In contrast, some of the challenges that arise from the implementation of work teams in organizations include loss of individual motivation, reduction of cooperation, communication problems, social loafing, conflict between members, difficulty in reaching consensus, and loss of individual responsibility for tasks (Steiner 1972; Ehrlenspiel et al. 1997; Mueller 2012; Halpin & Bergner 2018; Peltokorpi & Niemi 2018). These factors can negatively impact team performance and consequently the performance of the organization as a whole.

The implementation of a teamwork strategy can be beneficial to the performance of the organization, but if the team design and challenges associated with this kind of setting are not managed properly, the implementation of such a strategy can be self-defeating for the organization. Thus, the topic of teamwork has been a focus of interest for numerous studies dedicated to exploring the benefits and challenges of applying this strategy in different organizational settings, the different factors that impact system performance when a teamwork strategy is applied, and the development of approaches to effectively address the team design and teamwork implementation in order to maximize the benefit obtained from this work strategy.

Most of the existing literature related to teamwork focuses on observational studies to understand the factors that affect team performance and how this impact changes across different organizational settings. Team size, task type, reward system, workforce heterogeneity, and team synergy are some of the factors that have been recognized as significant for team performance (Steiner 1972; Erez & Somech 1996; Drach-Zahavy & Somech 2002; Doolen et al. 2003; Mueller 2012; Jaca et al. 2013; Peters & Carr 2013; Peltokorpi & Niemi 2018). Although extensive studies have focused on understanding the factors affecting the implementation of work teams in organizations, the extension of these studies to applications related to team design and team formation has received less attention. This dissertation thus aims to expand the knowledge pertaining to teamwork, expanding it to applications within the field of operations research. The main focuses of this work are the exploration of the impact of teamwork dynamics on system performance and the application of this knowledge to team design and team formation problems. The study will provide a basis for the development of mathematical models to address the team formation problem as part of operations research applications and will also help develop insight to guide managers in making decisions about team design and the design of workforce management plans, considering the effect of teamwork dynamics on system performance.

1.2 Current Study

This dissertation aims to study the team formation problem, considering the effect of team dynamics on individual productivity and consequently on system performance. The study of the team formation problem in this work is mainly focused on the team sizing problem, which involves determining the effect of the team size on system performance, considering team dynamics as a function of team size. The effect of team dynamics is considered in terms of the gains obtained from the effect of knowledge transfer between workers on individual productivity as well as the losses in productivity resulting from coordination and motivational issues that arise in teamwork settings. When additional members are added to a team, the available human resources and the available knowledge within the team to perform the specific task increase. However, at the same time, the addition of a member to the team will impact the coordination and relation links required to efficiently perform the task, as well as the individual motivation and perception of support availability among workers who are part of the team, causing actual team performance to fall below potential team performance. As a result, questions arise around the decision to increase the team size, considering that this decision will increase the available knowledge and human resources for the team to perform a task but also decrease the team productivity generated by coordination, relational, and motivational processes. This work aims to consider the effects of knowledge transfer and process loss in decisions related to team formation, specifically focusing on team sizing decisions, in order to provide managerial insight for the design and implementation of teamwork policies in different organizational settings. The remainder of the dissertation is organized as follows:

Chapter 2 addresses the grouping-assignment of heterogeneous workers in different cellular manufacturing structures while considering between-cell heterogeneity, grouping size, and system size as organizational factors. In this study, the effect of knowledge transfer is considered as part of the team dynamic effect that results from working together in a common cell. Different organizational factors are investigated as part of this study to evaluate their impact on system performance and their relevance to the worker-cell assignment problem. A key contribution of the current study is the demonstration of the value of considering these factors as part of the workforce planning process in a cellular manufacturing setting.

Chapter 3 explores the effect of team size on team performance in an experiential learning environment, considering knowledge transfer and process loss simultaneously. The study, which is developed through a simulation experiment, considers the team formation problem, specifically focusing on team sizing decisions. A single team-based setting is explored in this work, considering three different types of tasks: disjunctive, conjunctive, and additive. Managerial implications are derived to help organizations make decisions about the design and application of team-based work strategies in different organizational settings.

Chapter 4 investigates the team formation problem considering the simultaneous effect of knowledge transfer and process loss on team performance and consequently on system performance within an enterprise organizational context. The team formation problem is considered specifically from the perspective of team sizing decisions. A mathematical expression is introduced in this chapter to determine the optimal team size without solving the MNLIP for the team formation problem, thereby mitigating some of the computational complexity associated with the problem being defined as a nonlinear optimization problem.

Chapter 5 presents the general conclusions of this work and explores future research areas that could be derived though the studies presented in this dissertation.

CHAPTER 2

Worker-Cell Assignment: The Impact of Organizational Factors on Performance of Cellular Manufacturing Systems

Abstract

This study addresses worker-cell assignment of heterogeneous workers in various cellular manufacturing structures while considering between-cell heterogeneity, cell size, and system size as organizational factors. Workforce heterogeneity is considered based on individual learning characteristics, which include individual learning by doing and learning by knowledge transfer. Prior research demonstrated the impact of knowledge transfer on system performance as part of the assignment of workers. However, research related to the worker-cell assignment considering workforce heterogeneity and knowledge transfer is scarce. In the current study, different organizational factors are investigated to evaluate their effects on system performance and their relevance for the worker-cell assignment problem. This work contributes to the development of managerial insights to assist organizational managers in workforce management decisions in scenarios where more complex mathematical optimization methods are impractical.

2.1 Introduction

The worker assignment problem has been a long-standing topic of interest in the field of combinatorial optimization (Hefner et al. 1997; Dell' Amico & Toth 2000; Pentico 2007), as well as from the standpoint of organizational management (Valeva et al. 2007; Valls et al. 2009; Ward et al. 2013). The worker assignment problem is generally defined as the assignation of n types of tasks to m workers for each time period within a specific time horizon in order to optimize a specific objective function (Pastor & Corominas 2007; Wolsey & Nemhauser 2014). Several studies have been conducted in the literature related to the worker assignment problem, defined in different contexts and addressing the problem with a wide range of techniques. Most studies related to the worker assignment problem have defined it as a linear optimization problem, which for itself represents a challenging problem to solve, even for small instances (Dell' Amico & Toth 2000; Nembhard 2007; Dress et al. 2007). The complexity of this problem increases when nonlinear terms are added to the mathematical formulation, which is the case when considering workforce heterogeneity as function of the individual's learning capacity and previous experience on a specific task (Hewitt et al. 2015). Most work in this area has focused on the development of algorithms and techniques to increase the existing solution capacity to solve larger instances of the worker assignment problem. However, the consideration of learning by knowledge transfer, as well as other organizational factors like system dimensionality, manufacturing structure, and task complexity, has been examined far less thoroughly. Although the significance of these factors has been suggested in the literature, studies related to the worker assignment problem that considers these factors as part of the mathematical modeling are scarce (Nembhard 2000; Nembhard et al. 2002; Powell 2000; Wang et al. 2010; Nembhard et al. 2015).

The present study addresses the worker assignment problem of heterogeneous workers in a cellular manufacturing setting considering different organizational factors such as system size, cell size, between-cell heterogeneity, and knowledge transfer effects. Different cases of between-cell and within-cell manufacturing structures are also considered as part of the study. The individual worker production rate is modeled as a function of the individual worker capacity to learn by doing and by knowledge transfer.

We address four research questions in this study: (1) How does the consideration of knowledge transfer for the worker-cell assignment impact system efficiency across a range of cellular system structures? (2) How does the consideration of between-cell heterogeneity in addition to workforce heterogeneity impact production system efficiency? (3) What is the effect of system configuration dimensionality on system efficiency, where system dimensionality is a function of cell size and the number of cells in the production system? (4) Which factors have the largest impact in the worker-cell assignment: knowledge transfer, between-cell heterogeneity, cell size, or the number of cells in the production system? Contributions of this work include the development of knowledge on the value of considering these organizational factors as part of workforce management modeling in cellular manufacturing configurations. These factors have not previously been studied simultaneously as part of the assignment of workers in a cellular manufacturing setting.

The present work is structured as follows: Section 2 presents a literature review focused on existing works that consider factors such as workforce heterogeneity, between-cell heterogeneity, system dimensionality, and knowledge transfer as part of the definition of the worker assignment problem. Section 3 describes the simulation setting used in this study, as well as the implemented experimental design. In Section 4, a discussion of the most relevant results is presented. Lastly, the conclusion and further directions are presented in Section 5.

2.2 Literature Review

Workforce planning is a process used to trace strategic plans in organizations, specifically focused on making appropriate decisions about the workforce, aligned with organizational needs (Ward et al. 2013). Ward et al. (2013) discuss the importance of the workforce and the capacity of the organization to use it as a critical factor for the success of an organization. Several studies have been related to the workforce planning process, addressing a range of problems related to this topic. For the current study, the focus of interest is in the workforce planning literature related to the worker-task assignment problem, specifically for cellular manufacturing systems.

Worker-Assignment Problem

The worker-task assignment problem consists of determining the best way to assign the available workforce to different tasks in a system in order to attain a specific system output or optimize a specific performance measure. In general, the worker-assignment problem has been described considering the minimization of the total assignation cost as the objective function and a cost matrix for the different worker-task assignment possibilities (Dell'Amico et al. 2000; Pentico 2007; Ozbakir et al. 2010; Majumdar et al. 2012; Kaur et al. 2016). However, often measures other than cost are of interest in more realistic management scenarios, such as system productivity, workload balancing, or organizational profits (Norman et al. 2002; Dewi et al. 2015; Hewitt et al. 2015; Nembhard et al. 2015; Kaur et al. 2016; Zacharia et al. 2016). Similarly, in some scenarios, the worker-task assignment problem has been adapted to consider workforce heterogeneity based on metrics other than worker-task assignation cost, such as worker-task compatibility (Heirmel et al. 2010; Othman et al. 2012; Mutlu et al. 2013; Niakan et al. 2016; Feng et al. 2017), individual productivity based on constant production rates (Norman et al. 2002; Miralles et al. 2008; Blum et al. 2011; Mutlu et al. 2013; Benavides et al. 2014; Dupuy 2015; Ramezanian et al. 2015; Oksuz et al. 2017), or the individual production rate as a function of individual learning characteristics and cumulative experience (Corominas et al. 2010; Thongsanit 2010; Nembhard et al. 2012; Kim et al. 2013; Hewitt et al. 2015; Nembhard et al. 2015; Jin et al. 2016; Liu et al. 2016; Korytkowski 2017; Valeva et al. 2017).

For cases where worker-task compatibility has been used to model workforce heterogeneity, the literature typically assumes an available workforce with certain kinds of skills or limitations in performing specific tasks (Heirmel et al. 2010; Othman et al. 2012; Mutlu et al. 2013; Niakan et al. 2016; Feng et al. 2017). Based on the available skills/limitations per worker and the machines' requirements, the workers are assigned, wherein training is allowed to capacitate workers with additional skills leading to additional costs (Othman et al. 2012; Niakan et al. 2016; Feng et al. 2017). Similarly, in cases where workforce heterogeneity has been modeled using individual constant production rates, generally an available workforce is defined by differentiating the workers with different skill levels (Norman et al. 2002; Miralles et al. 2008; Blum et al. 2011; Mutlu et al. 2013; Benavides et al. 2014; Dupuy 2015; Ramezanian et al. 2015; Oksuz et al. 2017). The skill levels are paired with processing times for each different task. The production rates per task are constant and do not improve or lessen with the experience of performing or not performing the task. However, in some cases, additional training is allowed to increase the skill levels of the workers, incurring an additional cost (Norman et al. 2002).

For the cases where workforce heterogeneity has been modeled based on individual learning characteristics, the assignment problem is addressed considering a workforce composed of individuals with different learning parameter values

(Corominas et al. 2010; Thongsanit 2010; Nembhard et al. 2012; Kim et al. 2013; Hewitt et al. 2015; Nembhard et al. 2015; Jin et al. 2016; Liu et al. 2016; Korytkowski 2017; Valeva et al. 2017). The learning parameter values determine the individual production rate capacity and the impact of the gained experience of repeatedly performing a specific task. A range of models have been used to address the workforce planning problem in the literature, considering the individual production rate as a function of individual learning characteristics and cumulative experience (Anzanello et al. 2011).

In addition to the individual learning process resulting from the gained experience of repeatedly performing a task, previous work has also proposed the effect of worker interactions on individual worker productivity. This concept has been recognized in the literature as team synergy (Askin et al. 2001; Fitzpatrick et al. 2005; Liemhetchrat et al. 2014), team connectivity (Dorn et al. 2011), interpersonal relationship (Gutiérrezet al. 2016), transfer of learning (Olivera et al. 2004), informal team learning (Sibarani et al. 2015), or knowledge transfer/ knowledge sharing (Tomas-Hunt et al. 2003; Kurtulus 2011; Nembhard and Bentefouet 2015, Jin et al. 2018). Much of the work related to this topic focuses on understanding the factors that affect worker interaction within teams and explaining the effect of these factors at a theoretical level on the individual and work team's performance (Tomas-Hunt et al. 2003; Olivera et al. 2004; Kurtulus 2011; Sibarani et al. 2015). Although studies have investigated the impacts of worker interaction on individual worker performance, workforce planning models that consider such interactions and relationships remain scarce.

Several studies have addressed worker-team formation as part of the workforce planning process. Some of these studies have addressed team formation based on team skills requirements (Slomp et al. 2005; Wi et al. 2009; Perron 2010; Agustín-Blas et al. 2011; Pitchai et al. 2016), without considering the workers' interaction as part of the worker-assignment process. Other studies have addressed worker team formation considering workers' interaction (Askin et al. 2001; Fitzpatrick et al. 2005; Dorn et al. 2011; Liemhetchrat et al. 2014; Nembhard and Bentefouet 2015; Gutiérrezet et al. 2016; Jin et al. 2018). However, most of them consider worker interaction as a binary or nominal variable (Askin et al. 2001; Fitzpatrick et al. 2005; Dorn et al. 2011;

Liemhetchrat et al. 2014; Gutiérrezet al. 2016). This means that these studies do not consider the direct effects of worker interaction on individual worker productivity. Nembhard and Bentefouet (2015) conducted perhaps the first study to propose a mathematical approach to address workforce planning considering the direct effect of worker interaction on the individual worker productivity. This study considers worker interaction through the modeling of learning by knowledge transfer, which refers to the improvement on the individual worker performance through the interaction and experience of sharing with other people performing similar tasks. The study was extended by Jin et al. (2018), where a reformulation technique was applied to overcome the complexity of solving the nonlinear mathematical formulation that results from considering workforce heterogeneity as function of the individual learning by doing and knowledge transfer.

Shafer et al. (2001) discussed the impact of the consideration of workforce heterogeneity on system productivity, concluding that the non-consideration of workforce heterogeneity results in a systematic underestimation of system productivity. Similarly, Nembhard and Bentefouet (2015) incorporated the formation of work teams as part of the worker-assignment problem, considering worker interaction through the modeling of learning by knowledge transfer and showing the significance of considering the workers' interaction as part of the worker assignment problem. Nembhard and Bentefouet (2015) focused on pure serial and parallel manufacturing structures.

Worker-Cell Assignment Problem

Many studies related to the worker-assignment problem have focused on methodological development to increase the size of problem instances extant in the literature (Li et al. 2008; Mahdavi et al. 2010; Aalaei et al. 2014; Hewitt et al. 2015; Chunfeng et al. 2016; Karthikeyan et al. 2016; Niakan et al. 2016; Fichera et al. (2017); Jin et al. 2018). However, literature related to the effect of organizational factors on system performance as part of the worker assignment problem is not abundant, particularly for cellular manufacturing configurations, which are the primary interest of this study. In this work, we investigate the effects of some organizational factors as part of the worker-cell assignment problem, such as system dimensionality, system structure, and between-cell heterogeneity in addition to considering workforce heterogeneity and the effect of worker interactions. Cellular manufacturing configurations contain tasks that share similarities in their processes providing an environment for workers to learn from colleagues co-located in a cell. Workers can obtain some knowledge from these co-located workers, improving their own performance, and thereby the performance of the cell.

Much of the literature related to cellular manufacturing systems focuses on the design and implementation of cellular systems from the perspective of jobs and machines groupings. The exploration of the worker-assignment problem in the context of cellular manufacturing systems has been limited, specifically considering workforce heterogeneity based on the workers' ability to learn and improve the individual performance through the experience performing a task. Many studies of cellular manufacturing systems that address the worker assignment problem consider the concept of workforce heterogeneity define it based on individual constant production rates (Aalaei et al. 2014), worker time availability (Mahdavi et al. 2010; Aalaei et al. 2014; Niakan et al. 2016), worker assignment cost (Li et al. 2008; Niakan et al. 2016), and worker type making reference to workers' skills (Norman et al. 2002; Mahdavi et al. 2010; Niakan et al. 2016).

Liu et al. (2019) and Fichera et al. (2017) address the worker assignment problem considering workforce heterogeneity based on the individual workers' ability to learn by doing in a cellular manufacturing setting. Liu eta al. (2019) propose a heuristics method to address the worker assignment problem in cellular manufacturing systems considering the workers' performance as function of the individual's learning capacity, the cumulative experience and the forgetting effect. Also, the study incorporates the consideration of organizational factors such as system dimensionality, which was based on the number of cells in the system and the number of workers assigned per cell. However, the study did not consider the effect of workers interaction in the individual performance and the complexity of tasks that composed the cells. Similarly, Fichera et al. (2017) proposes a heuristic evolutionary method to address the worker assignment problem considering the workforce heterogeneity based on the effect of the individual learning characteristics and individual experience. The study considers system dimensionality as well but only based on the number of workers and tasks assigned per cell. We note that the study did not extend the mathematical model to incorporate the effect of workers' interaction nor to consider parameters related to task complexity and the number of cells that composed the system.

Sengupta & Jacobs (2004) and Asking & Huang (2001) explore the effects of team formation considering worker interactions in cellular manufacturing configurations. Sengupta & Jacobs (2004) compare the implementation of a cellular manufacturing configuration against other manufacturing structures and discuss its advantages when considering the effect of teamwork. The study models the effect of workers' interaction within the cell considering the decrease in the time required for a worker to perform a task as result of the help of co-workers assigned to the same cell. Neither workforce heterogeneity nor the assignment of workers is considered in that study. Asking & Huang (2001) address the team formation for cellular manufacturing settings considering workers interaction based on the concept of synergy. However, the study did not consider the impact workers' synergy as part of the individual performance.

The exploration of the worker-assignment problem for cellular systems, considering simultaneously the properties of the production system design based on system dimensionality, system structure, and cells heterogeneity in addition to the consideration of workforce heterogeneity as function of the individual learning capacity, task experience, and workers interaction, have not been address previously in the literature. The current work focuses on addressing this gap, examining the worker assignment problem in the context of cellular manufacturing with individual worker learning and knowledge transfer, in addition to physical properties of the production system design, such as system dimensionality, system structure, and between-cell heterogeneity. The worker assignment problem for the described context will be refer in this work as the worker-cell assignment problem, emphasizing that the study focuses specifically in cellular configurations.

Studies have investigated some of the aforementioned organizational factors, although not in the context of cellular manufacturing systems. Wang et al. (2010)

examined the effect of system complexity resulting from different manufacturing system configurations on system performance, which for this case was measured using the system throughput. The manufacturing system configurations were defined as hybrids of serial and parallel manufacturing structures. Powell (2000), investigated team size and task division for a serial manufacturing configuration. The model proposed focused on providing insight about which scenarios are better suited to assigning specialized workers to simple tasks, or to assigning more complex tasks to large teams. The study modeled serial production configurations and did not address the worker assignment problem.

The effect of task complexity has also been explored. Nembhard (2000) investigated the effect of task complexity on the mean of the individual learning and forgetting parameters of the worker productivity model. The results showed that when the complexity of a task increases, both the asymptotic steady-state performance level (k) and the initial performance (p) parameters decrease. In contrast, when the complexity of a task increases, the value of the learning rate parameter (r), also increases. Nembhard et al. (2002) investigated the effect of task complexity on the individual learning and forgetting parameter distributions. The study showed that the task complexity significantly affects the variance of the learning and forgetting parameters, where higher levels of complexity result in higher variability of the learning/forgetting parameters. Studies focused on exploratory analysis of these factors are scarce, particularly for cellular manufacturing scenarios.

2.3 Methodology

This study addresses the worker-cell assignment problem for heterogeneous workers on tasks of varying complexities. The heterogeneity of workers is considered, estimating worker performance as a function of the individual capacity to learn by doing and by knowledge transfer. A simulation experiment is used along with a range of organizational factors such as system size, cell size, and between-cell heterogeneity. The effect of the consideration of knowledge transfer is also explored. This study addresses questions related to the impact of these factors for the worker-cell assignment problem. Details of the simulation experiment and data used are described below.

Simulation Experimental Scenario

In this study we construct a series of simulations using MATLAB™ considering four different cases of cellular manufacturing configurations and four experimental factors, as illustrated in Figure 1. The simulation design includes a time horizon of 50-time periods and assumes a production system with unspecified demand characterized by tasks with unconstrained input. For example, JIT systems controlled by a pull strategy may have this behavior when operating at steady-state. Thus, the system will produce as much as possible in the 50 periods, unconstrained by material resources. Similarly, the study considered only one product type with a skilled workforce for all the available tasks. Worker assignments were not restricted by skill levels or skill types, and each worker has the capability to perform any task. The dependency between tasks was defined by the system configuration.

Individual worker performance is simulated considering the individual capacity to learn by doing with parameters k, p, and r, and by knowledge transfer, with parameter θ. Details about the estimation of the workers' performance will be discussed in the following subsection. The simulation scenario consists of a production system defined by four different cellular manufacturing configurations as cases, an available pool of workers as an input based on the number of tasks in the system considering one worker assigned per considered task, and a set of experimental factors that will be defined later in this section (Figure 2.1). The simulation output is system efficiency, defined as the average output per worker. The model to be used for the analysis of results is a General Linear Model.

The four cellular manufacturing configurations considered include: Case I) a pure parallel system, with a parallel structure between and within manufacturing cells (Figure 2.2); Case II) a hybrid serial-parallel system, with a serial structure between manufacturing cells and parallel structure within manufacturing cells (Figure 2.3); Case III) a hybrid parallel-serial system, with a parallel structure between manufacturing cells and serial structure within manufacturing cells (Figure 2.4); and Case IV) a pure serial system, that is, a serial structure between and within manufacturing cells (Figure 2.5).

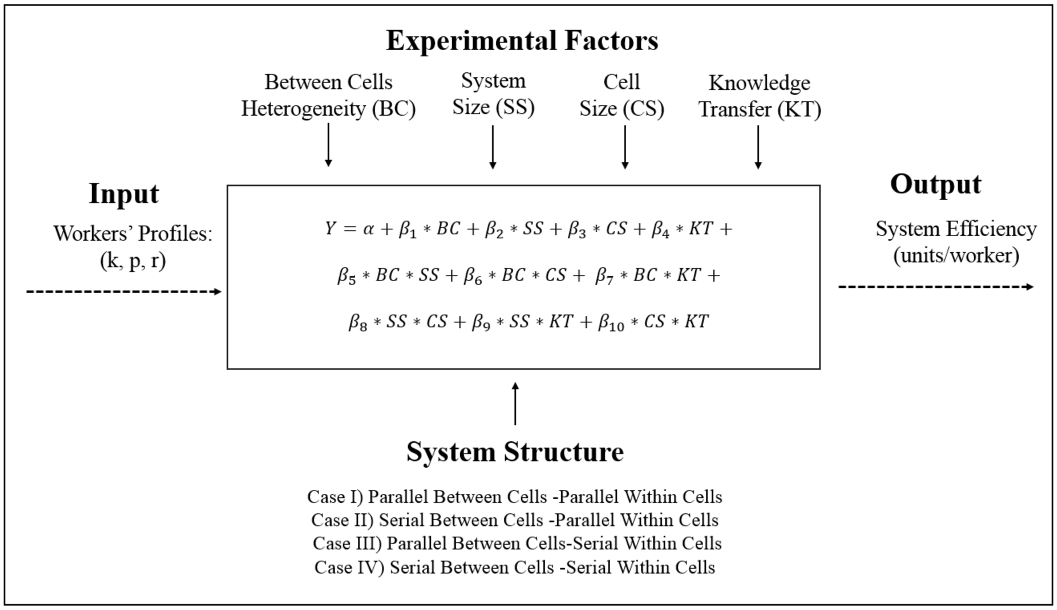

Figure 2.1. Simulation Schema

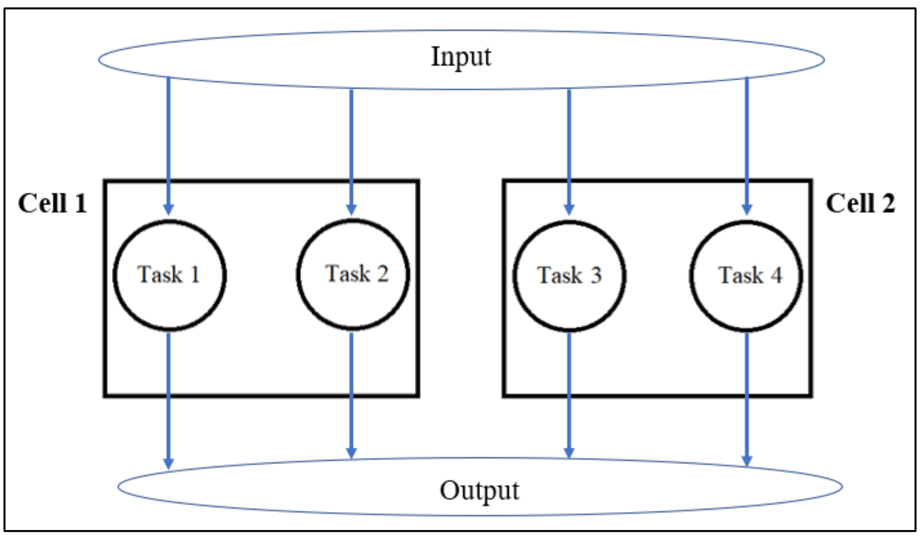

Figure 2.2. System Structure for Case I. Parallel Structure between Cells – Parallel Structure within Cells.

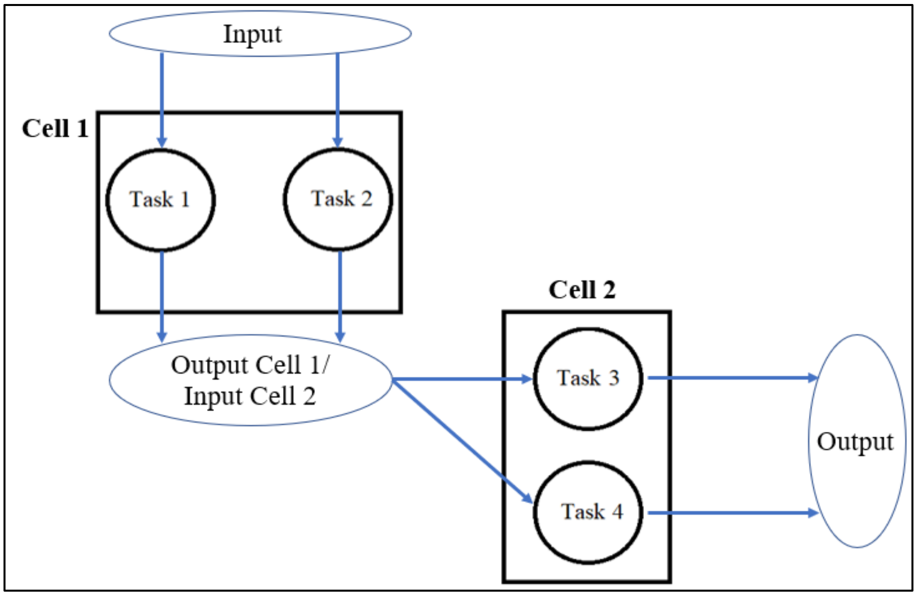

Figure 2.3. System Structure for Case II. Serial Structure between Cells – Parallel Structure within Cells.

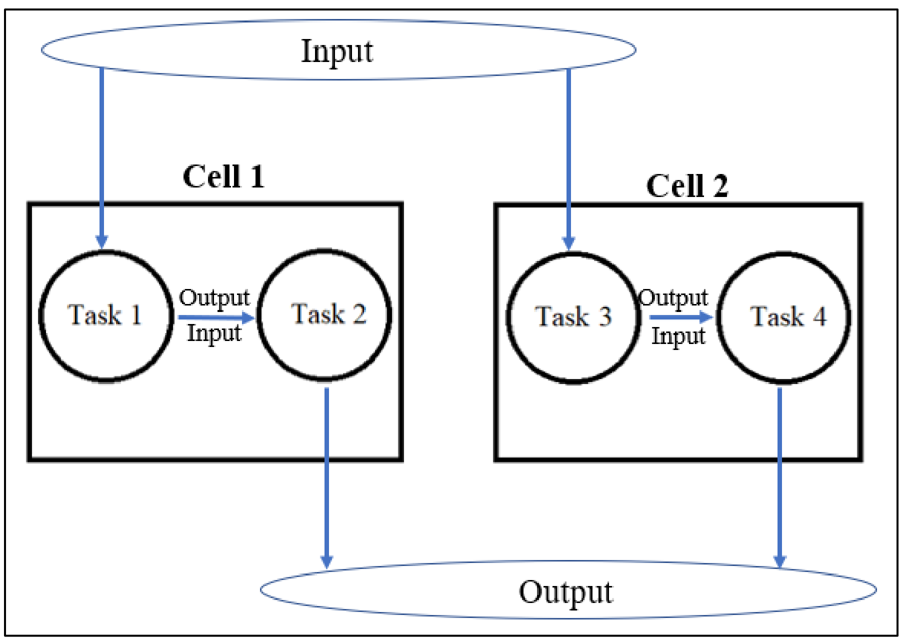

Figure 2.4. System Structure for Case III. Parallel Structure between Cells – Serial Structure within Cells.

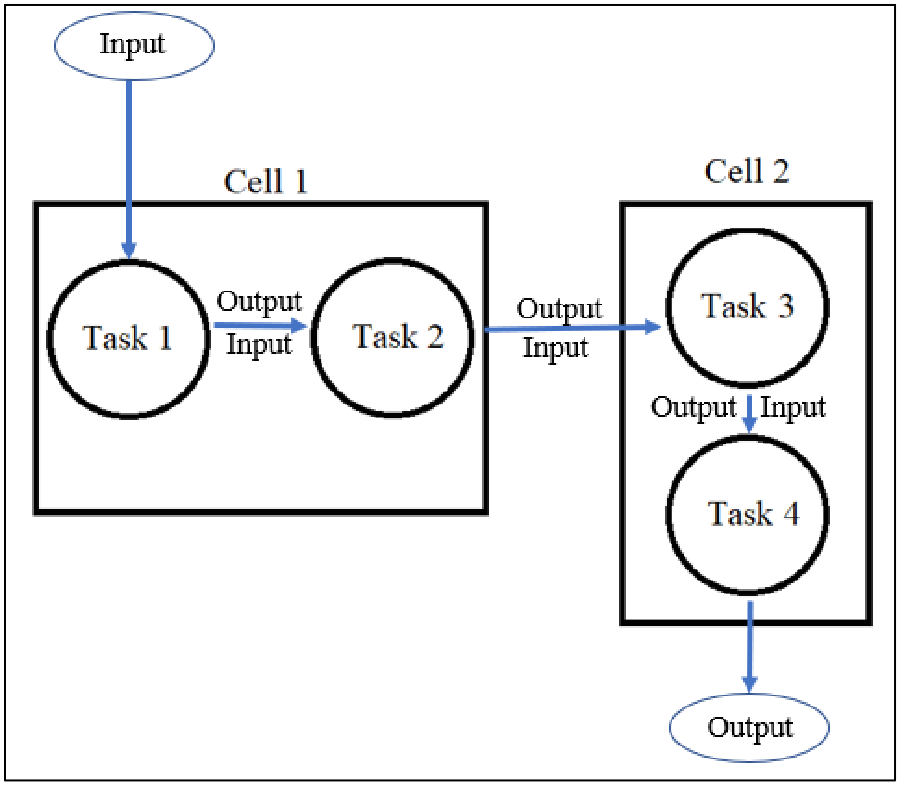

Figure 2.5. System Structure for Case IV. Serial Structure between Cells – Serial Structure within Cells.

A full factorial design is used to examine the set of organizational factors in Table 2.1, with each factor evaluated at two levels. The factors include: Between-cell heterogeneity (BH), System Size (SS), Cell Size (CS), and Knowledge Transfer (KT). A total of 16 experimental runs are evaluated for each of the cases of cellular manufacturing configurations consisting of 100 replications for each treatment.

For the between-cell heterogeneity (BH) factor, two experimental levels are considered. The first level is the case of low variability between task complexities, where the rank complexities associated with the cells had a standard deviation of 0 units and a rank mean of 1 unit. The second level of this factor is high variability between task complexities, where the complexities of the cells for this level had a standard deviation of 0.6 units and a rank mean of 1 unit. For the case of low heterogeneity between cells, a complexity rank of 1 unit is assigned to each cell in the production system. For the case of high heterogeneity between cells, a different complexity rank is assigned for each cell, considering the specifications of standard deviation and mean defined as part of the experimental design. Specifically, complexity rank values of 0.4 units and 1.6 units are assigned to cell 1 and cell 2, respectively, in the production systems composed of two manufacturing cells. For the production systems composed of three manufacturing cells, complexity ranks of 0.5102 units, 0.6450 units, and 1.84 units are assigned to cell 1, cell 2, and cell 3, respectively. The complexity values assigned to the manufacturing cells were used to generate the parameters of the worker profiles corresponding to the tasks contained in each cell. The main objective of the examination of the BH factor was to investigate the impact of between-cell heterogeneity on system performance, which for this study was defined as system efficiency.

In order to evaluate the effect of the system configuration dimensionality on the system performance, the factors of system size and cell size were examined. For the factor of System Size (SS), two experimental levels were considered, consisting of two or three cells. Similarly, for the factor of Cell Size (CS), two experimental levels were considered. The low level evaluated for the CS factor was defined as a production system where each manufacturing cell is composed of two tasks and consequently involves two workers per cell in each time period. For the high level of CS, the simulated scenario was defined as a production system where each manufacturing cell is composed of three tasks and consequently involves three workers assigned per cell. The main objective of the examination of these factors is to investigate the effect of system configuration dimensionality on system performance.

The fourth factor is Knowledge Transfer (KT), with two experimental levels. The low level assumes zero knowledge transfer between workers, and the high level was the consideration of empirically informed distributions of knowledge transfer as part of the estimation of the individual worker's productivity. The objective examining this factor is to investigate the impact of knowledge transfer on the system performance for different manufacturing configuration structures.

The worker-cell assignment problem was addressed primarily through the simulation of the complete enumeration space for tractable scenarios. For cases where the simulation of the complete enumeration space was not achievable within a maximum computational time of 72 hours, a metaheuristic optimization method, specifically a genetic algorithm (Appendix 2-A), was implemented. Information associated with the system efficiency was collected and analyzed as an indicator of the system performance, with efficiency defined as the average output per worker. The system efficiency was used to correct for the scaling of larger systems, such that the comparison between systems of different dimensions are relatable (SS and CS). That is, differences in efficiency are informative of how these systems perform on a per worker basis.

Table 2.1: Experimental Design.

Factors	Levels
BH: Between-cell heterogeneity	Low (StDev = 0), High (StDev = 0.6)
SS: System Size (# cells)	Low (2 cells), High (3 cells)
CS: Cell Size (# workers/cell)	Low (2 workers/cell), High (3 workers/cell)
KT: Knowledge Transfer	Low (0%), High (100%)

Workers' Production Rate Simulation

For the estimation of the individual worker performance, the mathematical model described in Equation (2.1) was used as proposed in Nembhard and Bentefouet (2015). The model estimates the individual worker performance considering the effects of both learning by doing and learning by knowledge transfer.

$$y_x = k\left(\frac{\theta * T + x + p}{\theta * T + x + p + r}\right) \tag{2.1}$$

This model estimates the worker production rate considering workers' previous experience, represented by the parameter p, the amount of cumulative work x in a specific task, the steady state level k that will be achieved when the worker completes the learning process, and the cumulative production required to achieve a $k/2$ level of performance represented by the parameter r. The parameter θ and the variable T are related to the percentage of knowledge transferred from other workers performing similar tasks and the total cumulative knowledge of other workers, respectively. The model was a modification of the learning curve model developed by Mazur and Hastie (1978), to consider both the effect of learning by doing and the effect of learning by knowledge transfer in the workers' performances. The details about the generation of the corresponding model parameters are discussed below.

Input Data for the Simulation Experiment

An initial pool of workers' profiles was generated as previously described, where each worker profile consisted of a set of learning parameters (*k, p, r, θ*) for each different task. The size of the initial pool was determined by the total number of tasks that composed the manufacturing system considering specialized workers. Nembhard and Bentefouet (2015) discussed the main details of the model parameter fitting process (*k, p, r, θ*). An empirical dataset of 75 workers (Shafer et al., 2001) was used for this end, obtaining an average R^2 of 96% and a standard deviation of 2%. Through the fitting process, the authors modeled the parameters associated with Eq. 2.1 (*k*, *p*, *r*) using a Multivariate Normal Distribution with a mean and standard deviation presented in Table 2.2 (Nembhard & Shafer 2008). Similarly, the knowledge transfer parameter *θ* was modeled by a normal distribution with a mean of 0.644 and a variance of 0.409 (Nembhard and Bentefouet, 2015). For the present study, these values were assumed to be associated with a rank complexity equal to 1.

Table 2.2. Mean and Variance–Covariance Matrix for the Estimation of the Learning Parameters.

$\mu=\begin{bmatrix}\ln k\\ \ln p\\ \ln r\end{bmatrix}=\begin{bmatrix}3.34\\ 4.57\\ 4.73\end{bmatrix}$	$\sum = \begin{array}{cc} \begin{array}{c}\ln k\\ \ln p\\ \ln r\end{array} & \begin{bmatrix}0.730 & 0.341 & 0.336\\ 0.341 & 7.830 & 3.420\\ 0.336 & 3.420 & 4.020\end{bmatrix} \\ & \begin{array}{ccc}\ln k & \ln p & \ln r\end{array}\end{array}$

For task complexity, an initial pool of worker profiles was generated using the parameter distribution in Table 2.2 and then scaled by the assigned complexity rank, depending on the experimental scenario. Studies in the literature demonstrate that when the complexity of a task increases, both the asymptotic steady-state performance level (*k*) and the initial performance (*p*) parameters decrease (Nembhard, 2000). In contrast, in the case of the learning parameter *r*, when the complexity of the task increases, the value of that parameter also increases (Nembhard, 2000). Based on the conclusions of these studies, where the effect of complexity was related to the individual parameters, the parameters *k* and *p* corresponding to the tasks contained in a manufacturing cell were divided by the complexity rank assigned to the specific cell. For the scaling of the r parameter, the value generated with the distribution base (Table 2) was multiplied by the complexity rank assigned to the cell.

For example, assuming a manufacturing cell with a rank complexity of 0.4 units, an initial worker profile would be generated using the distribution base provided in Table 2.2, which is associated with a rank complexity of 1 unit. The values for the parameters k, p, and r, which were originally obtained from the random sampling of this distribution from Table 2, are 9.46, 41.70, and 108.04, respectively. These values would be scaled as previously discussed with the rank complexity, k = 9.46/0.4, p = 41.70/0.4, and r = 108.04*0.4. Finally, the obtained values k = 23.65, p = 104.25, and r = 43.22 represent the parameters associated with the corresponding cell with an assigned complexity rank of 0.4.

For the parameter associated with the knowledge transfer, a constant value was assumed for the different levels of rank complexity. This assumption was based on the fact that the parameter θ is multiplied in the equation by the quantity T that represents co-workers' cumulative experience on similar tasks, which are already affected by the task complexity. A constant value for the variance of the parameters through the different levels of task complexity is also assumed. In Nembhard and Osothsilp (2002), the effect of task complexity on the distribution of learning and forgetting parameters (k, p & r) was investigated. This study found that for inexperienced workers, the variance of the distribution of the k and r parameters changed with respect to the complexity of the task. However, as a simplification technique, the present study assumed a constant variance for all parameters (Table 2.2).

2.4 Results and Discussion

Several cases representing a range of production scenarios were investigated. The cases explored the assignment of workers in cellular manufacturing configuration, considering serial and parallel structures and their hybrid combinations between and within manufacturing cells. A General Linear Model ANOVA was considered for each case to compare the effects of the experimental factors. We used a Box-Cox transformation and a Weighted Least Squares ANOVA to normalize the data and avoid heteroscedasticity. Following this, we verified the ANOVA assumptions using a Kolmogorov-Smirnov test to assess normality, a Runs test for independence, and a Levene's test for homoscedasticity. Below, a discussion of the simulation results is presented for each case.

Case I. Parallel Between Cells – Parallel Within Cells

The first case represents a manufacturing system composed of a pure parallel configuration. The results of the ANOVA for this case are presented in Table 2.3. For this analysis, the system efficiency was considered as the dependent variable, defined as the average output per worker. The independent factors were Between-cell heterogeneity (BH), System Size (SS), Cell Size (CS), and Knowledge Transfer consideration (KT). For this manufacturing structure, the main effect of the factors of Between-cell heterogeneity, Cell Size, and Knowledge Transfer showed a significant effect for the considered performance measure at a confidence level of 95%.

For the Between-cell heterogeneity factor, defined by parallel structures between and within manufacturing cells, a significant difference in system efficiency is obtained when considering different levels of task heterogeneity between manufacturing cells. Specifically, for the instances where a low level of between-cell heterogeneity was considered, a lower system efficiency was obtained than in instances defined by higher levels of between-cell heterogeneity (Figure 2.6). Shafer et al. (2001) examined the effect of modeling task heterogeneity in the system productivity, wherein they showed that the scenario which considered high task heterogeneity resulted in a higher system output than the case with no heterogeneity, with a constant mean assumed. For the Cell Size factor, the results of our study showed that different cell sizes, defined as the number of workers per cell, significantly affected the system efficiency. Specifically, a system composed of cells with three workers per cell resulted in a higher system efficiency than systems composed of cells with two workers per cell. Finally, for the Knowledge Transfer factor, consideration, the results showed that the system efficiency was statistically different depending on whether knowledge transfer was considered as part of the worker assignment problem. The main effects showed that in instances where knowledge transfer between workers was considered, the system efficiency resulted in better performance (Figure 2.6).

When the impact of these factors was explored, the results showed that Between-Cell Heterogeneity explains the higher amount of variability associated with the system performance (Table 2.3). This means that for a production system considering a pure parallel configuration between and within manufacturing cells, Between-Cell Heterogeneity may have the largest impact in the worker-cell assignment.

The results similarly showed, that for this case, the significant second-order interactions included Between-cell Heterogeneity-System Size and Between-cell Heterogeneity-Cell Size. The interaction plots are shown in Figure 2.7. For each of these interactions, a *t*-test was performed to verify the significance of the difference in system performance for each of the interaction levels. A confidence level of 95% was used.

For the Between-cell heterogeneity-System Size interaction, BH*SS, the results showed that in instances of low heterogeneity between manufacturing cells, the system efficiency was not statistically different between systems composed of two and three manufacturing cells (*t*-test, $p = 0.138$). In contrast, for instances associated with high heterogeneity between manufacturing cells, a higher system efficiency was obtained for the production system composed of two manufacturing cells (*t*-test, $p = 0.022$). These results suggest that in production systems composed of a pure parallel configuration between and within manufacturing cells, as the heterogeneity between the cells increases, the consideration of the system size as part of the worker-cell assignment model becomes more critical.

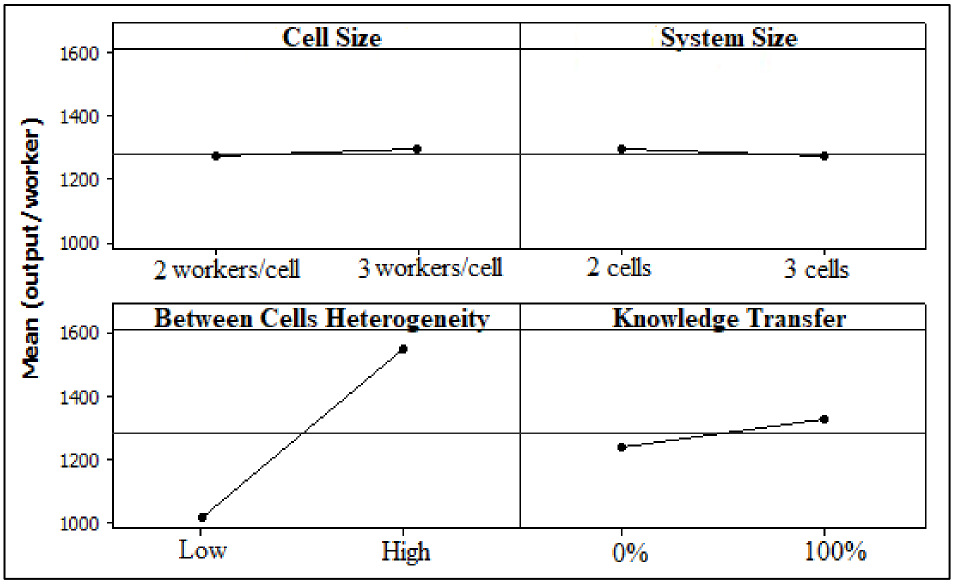

Figure 2.6. Main Effects Plot for Case I. Parallel Between Manufacturing Cells – Parallel Within Manufacturing Cells Structure.

Table 2.3. ANOVA for Case I: Parallel Between Manufacturing Cells – Parallel Within Manufacturing Cells Structure (dependent variable: efficiency [output/worker])

Source	d.f	SS (adj)	MS (Adj)	F	Pr > F
Between-Cell Heterogeneity (BH)	1	984.14	984.14	986.10	0.000**
System Size (SS)	1	0.24	0.24	0.24	0.621
Cell Size (CS)	1	6.22	6.22	6.23	0.013**
Knowledge Transfer (KT)	1	25.16	25.16	25.21	0.000**
BH*SS	1	8.58	8.58	8.60	0.003**
BH*CS	1	6.35	6.35	6.36	0.012**
BH*KT	1	2.73	2.73	2.74	0.098
SS*CS	1	0.00	0.00	0.00	0.988
SS*KT	1	0.74	0.74	0.74	0.388
CS*KT	1	0.33	0.33	0.33	0.564
Error	1589	1585.85	1.00		
Total	1599				

[Weighted Least Squares ANOVA with a significance level of 5%; R-Sq (Adj) = 39.74%; Box Cox Transformation with λ=0.32]

For the Between-Cell Heterogeneity-Cell Size interaction, BH*CS, the results showed that in instances of low heterogeneity between manufacturing cells, the manufacturing cells composed of two workers per cell resulted in a lower system efficiency than cells composed of three workers (*t*-test, p = 0.001). However, for instances of high heterogeneity between manufacturing cells, the system efficiency was not statistically different between production systems defined by manufacturing cells with two and three workers per cell (*t*-test, p = 0.965). These results suggest that in production systems composed of a pure parallel configuration between and within manufacturing cells, as the heterogeneity between the cells increases, the consideration of the cell size as part of the worker-cell assignment model becomes less important. Although the factor cell size had a significant impact on system efficiency in this case, this factor showed a considerably lower impact on system efficiency when is compared to other evaluated factors, and when evaluated across the levels examined within the factor. These results suggest that managers should prioritize the modeling and consideration of others factors such knowledge transfer and between cells heterogeneity over cell size.

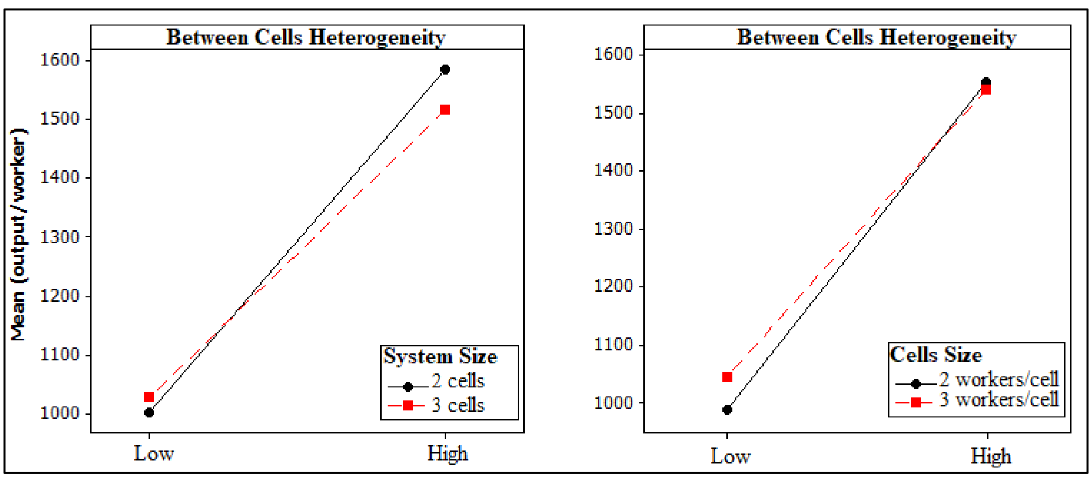

Figure 2.7. Interaction Plot for Case I. Parallel Between Manufacturing Cells – Parallel Within Manufacturing Cells Structure.

Case II. Serial Between Cells – Parallel Within Cells

Case II represents a hybrid manufacturing configuration, considering a production system defined by a serial structure between manufacturing cells and a parallel structure within the cells. For this case, the ANOVA showed that all of the factors except Between-cell heterogeneity had a significant effect on the system efficiency at a confidence level of 95% (Table 2.4). This suggests that for a production system defined by a serial structure between manufacturing cells and a parallel structure within the cells, a significant difference in system efficiency is obtained when considering different numbers of cells, different numbers of workers assigned to the cells, and the effect of knowledge transfer between workers. Specifically, for System Size, a higher system efficiency was obtained for instances of production systems composed of two manufacturing cells than for systems composed of three manufacturing cells (Figure 2.8). For the Cell Size factor, instances with production systems containing three workers per cell resulted in a higher system efficiency than the instances of production systems containing two workers per cell. Finally, a higher system efficiency was obtained for instances that considered Knowledge Transfer as part of the worker assignment problem addressed in this case (Figure 2.8). When the impact of the factors is compared for this case, the System Size factor explained the higher amount of variability associated with system performance. This suggests that for a production system considering a serial structure between manufacturing cells and a parallel structure within the cells, the factor of System Size has the largest impact in the worker-cell assignment considering the system efficiency as the performance measure.

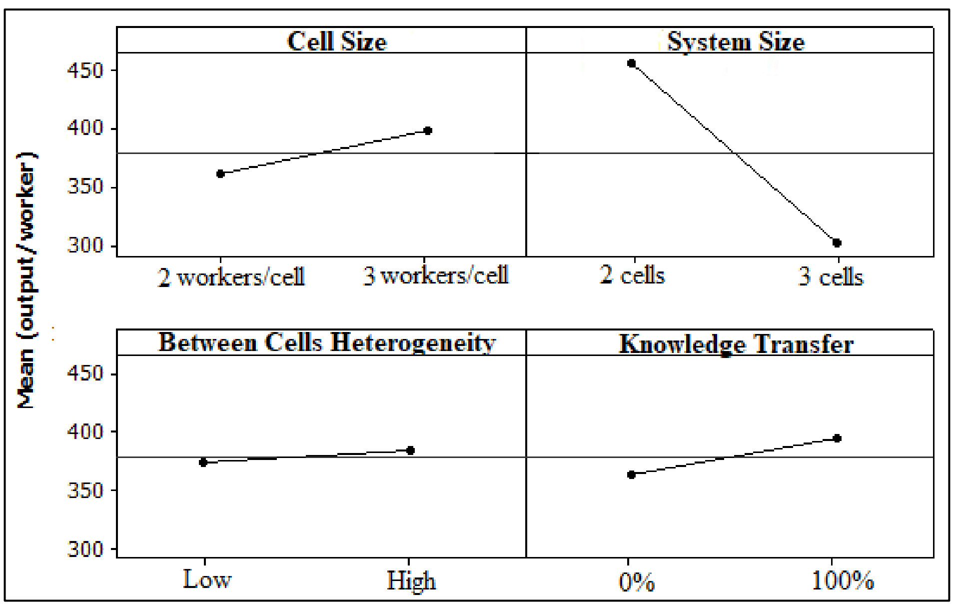

Figure 2.8. Main Effects Plot for Case II. Serial Between Manufacturing Cells – Parallel Within Manufacturing Cells.

Table 2.4. ANOVA for Case II: Serial Between Manufacturing Cells – Parallel Within Manufacturing Cells Structure (dependent variable: efficiency [output/worker])

Source	d.f	SS (Adj)	MS (Adj)	F	Pr > F
Between-Cell Heterogeneity (BH)	1	0.631	0.631	0.63	0.428
System Size (SS)	1	470.748	470.748	468.30	0.000 **
Cells Size (CS)	1	43.315	43.315	43.09	0.000 **
Knowledge Transfer (KT)	1	18.647	18.647	18.55	0.000 **
BH*SS	1	0.026	0.026	0.03	0.873
BH*CS	1	9.303	9.303	9.26	0.002 **
BH*KT	1	0.379	0.379	0.38	0.539
SS*CS	1	0.099	0.099	0.10	0.754
SS*KT	1	0.196	0.196	0.20	0.659
CS*KT	1	0.160	0.160	0.16	0.690
Error	1589	1597.298	1.005		
Total	1599				

[Weighted Least Squares ANOVA with a significance level of 5%; R-Sq (Adj) = 26.31%; Box Cox Transformation with $\lambda=0.35$]

When the second-order interactions between factors were analyzed, only the Between-Cell Heterogeneity-Cell Size, BH*CS, interaction was significant. Figure 2.9 and corresponding *t*-tests for this case indicate that the instances composed of production systems with three workers per cell did not show a significant difference in the system efficiency between scenarios of low and high between-cell heterogeneity (*t*-test, p = 0.174). However, for instances with two workers per cell, the production system results in a higher efficiency for the scenarios of high heterogeneity between manufacturing cells (*t*-test, p = 0.036). Thus, for production systems where the cells are composed of three workers per cells, considering a hybrid manufacturing system defined by a serial structure between manufacturing cells and a parallel structure within the cells, changes in between-cell heterogeneity, at the levels analyzed in this study, do not have a significant impact in the system efficiency. However, for production systems where the cells are composed of two workers per cells, the consideration of between-cell heterogeneity in the system was shown to be important. This may suggest that as the team size in the cells increases, the consideration of between-cell heterogeneity becomes less critical.

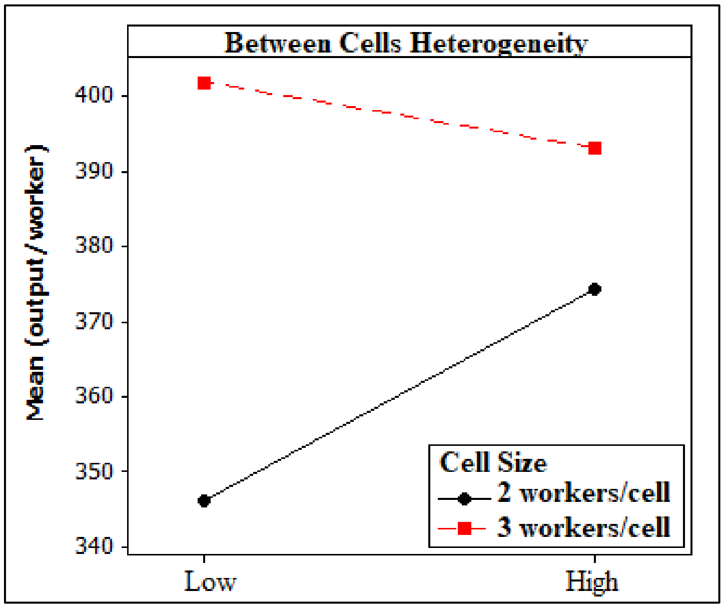

Figure 2.9. Interaction Plot for Case II. Serial Between Manufacturing Cells – Parallel Within Manufacturing Cells.

Case III. Parallel Between Cells –Serial Within Cells

Case III represents a hybrid manufacturing configuration, considering a production system defined by a parallel structure between manufacturing cells and a serial structure within the cells. For this case, the ANOVA showed that the main effects of all the factors, with the exception of System Size, were significant when the system efficiency was selected as the performance measure (Table 2.5). For a production system defined by a parallel structure between manufacturing cells and a serial structure within the cells, a significant difference in system efficiency is obtained when varying the number of workers assigned to the cells, the level of between-cell heterogeneity, and the consideration of knowledge transfer between workers.

As illustrated in Figure 2.10, the scenarios associated with a high level of between-cell heterogeneity resulted in a higher system performance than the scenarios in which the production system was defined with similar tasks. Similarly, for the Cell Size factor, the instances with production systems containing two workers per cell resulted in a higher system efficiency than the instances of production systems containing three workers per cell. The results obtained for this factor, in this case, are opposite to the results obtained in Case II, where a higher system efficiency was obtained for instances of production systems composed of three workers per cell. Finally, for the factor of Knowledge Transfer, a higher system efficiency was obtained in instances where Knowledge Transfer was considered as part of the worker assignment problem.

For this case, Cell Size explained the higher amount of variability associated with the system performance. Between-Cell Heterogeneity occupied the second position in the explanation of total variability associated with the system. This suggests that for a production system considering a parallel structure between manufacturing cells and a serial structure within cells, Cell Size has the largest impact in the worker-cell assignment, followed by Between-Cell Heterogeneity. These results indicate that although the consideration of all of the factors analyzed in this work is important, the consideration of Cell Size and Between-cell heterogeneity is more critical for the worker-cell assignment in a production system considering a parallel structure between manufacturing cells and a serial structure within cells.

Table 2.5. ANOVA for Case III: Parallel Between Manufacturing Cells –Serial within Manufacturing Cells Structure (dependent variable: efficiency [output/worker])

Source	d.f	SS (adj)	MS (Adj)	F	Pr > F
Between-Cell Heterogeneity (BH)	1	410.65	410.65	410.98	0.000 **
System Size (SS)	1	3.42	3.42	3.42	0.065
Cells Size (CS)	1	861.56	861.56	862.25	0.000 **
Knowledge Transfer (KT)	1	11.67	11.67	11.68	0.001 **
BH*SS	1	6.70	6.70	6.70	0.010 **
BH*CS	1	0.18	0.18	0.18	0.668
BH*KT	1	0.04	0.04	0.04	0.839
SS*CS	1	1.53	1.53	1.53	0.217
SS*KT	1	2.25	2.25	2.26	0.133
CS*KT	1	0.09	0.09	0.09	0.759
Error	1589	1587.73	1.00		
Total	1599				

[Weighted Least Squares ANOVA with a significance level of 5%; R-Sq (Adj) = 46.38%; Box Cox Transformation with λ=0.37]

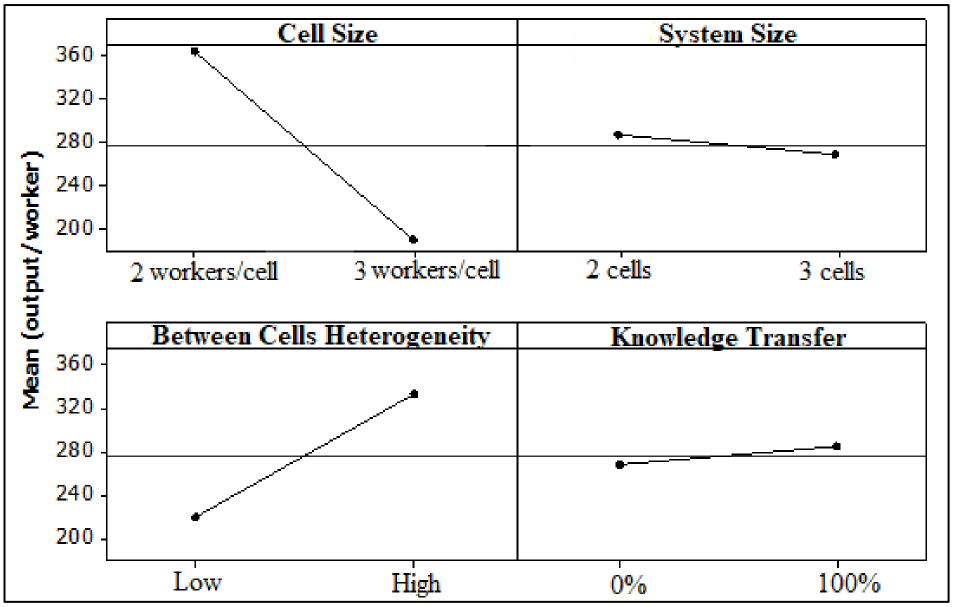

Figure 2.10. Main Effects Plot for Case III. Parallel Between Manufacturing Cells – Serial Within Manufacturing Cells.

For the second-order interactions in this case, only the Between-Cell Heterogeneity-System Size interaction, BH*SS, resulted significant (Table 2.5 and Figure 2.11). The results showed that for scenarios with low heterogeneity between manufacturing cells, no significant difference in system efficiency was found between production systems composed of two manufacturing cells and systems composed of three manufacturing cells (*t*-test, p = 0.724). In contrast, for scenarios of high heterogeneity between manufacturing cells, a higher system efficiency was obtained for production systems composed of two cells (*t*-test, p = 0.017). These results suggest that for this case, as the between-cell heterogeneity increases, the consideration of the number of cells in the manufacturing system becomes more critical for the worker-cell assignment, in which smaller systems resulted in a higher system efficiency.

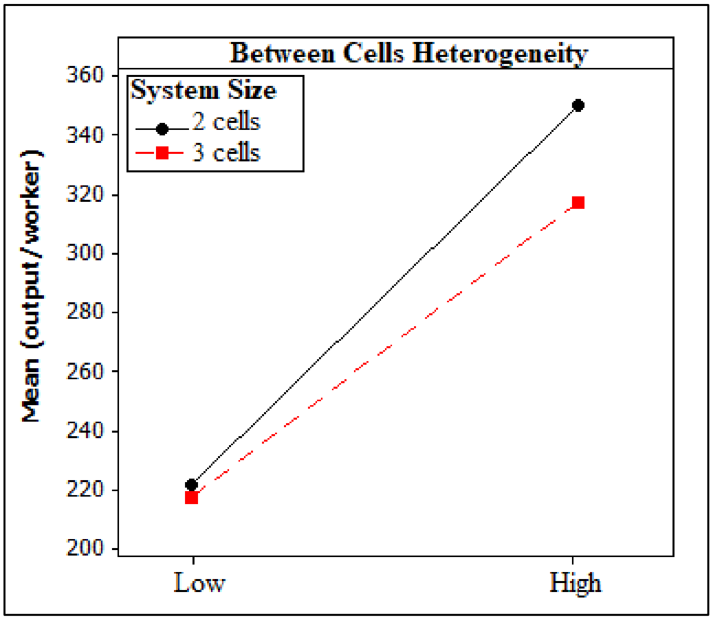

Figure 2.11. Interaction Plot for Case III. Parallel Between Manufacturing Cells – Serial within Manufacturing Cells.

Case IV. Serial Between Cells –Serial Within Cells

The fourth configuration represents a pure serial manufacturing system, which is defined by a fully serial structure both between and within manufacturing cells. For this case, the ANOVA showed that all of the factors were significant considering the system efficiency as the performance measure at a confidence level of 95% (Table 2.6). This suggests that for production systems defined by a pure serial structure, a significant difference in system efficiency is obtained when considering different levels of system size, cell size, between-cell heterogeneity, and percentage of knowledge transfer between workers.

The main effects of the factors showed a similar tendency as in Case III, where higher levels of between-cell heterogeneity were associated with a higher system performance, considering the system efficiency as the performance measure (Figure 2.12). For System Size, the instances where the systems were composed of two manufacturing cells performed better in terms of system efficiency than the systems composed of three manufacturing cells. Similarly, for Cell Size, the instances where the production systems were simulated considering smaller team size in the cells resulted in a higher system efficiency than instances of production systems composed of larger team size. Finally, a higher system efficiency was obtained in instances where Knowledge Transfer was considered as part of the worker assignment problem.

Related to the impact of the factors in the system performance for this case, the ANOVA showed that the Between-Cell Heterogeneity explained the higher amount of variability associated with the system. This means that for a production system considering a pure serial structure between and within manufacturing cells, the factor of between-cell heterogeneity has the largest impact on the system efficiency as part of the worker-cell assignment.

For the second-order interactions, three interactions were significant: System Size-Cell Size, Knowledge Transfer-Between-Cell Heterogeneity, and Knowledge Transfer-Cell Size (Table 2.6 and Figure 2.13). In order to parse the significantly contrasting levels for the interactions, the contrasts were analyzed using *t*-tests). For the System Size-Cell Size interaction, the results showed that for this case, the system efficiency was significantly different between systems composed of different numbers of cells (*t*-test, $p = 0.000$). Consistently, smaller systems in terms of both the number of cells that composed the system and the number of workers assigned to each manufacturing cells resulted in a better system efficiency for this case. These results suggest that for pure serial manufacturing configurations, a smaller system dimensionality in terms of the number of manufacturing cells and team size in the cells would be preferred, in order to obtain a higher system efficiency, defined as the output per worker.

Table 2.6. ANOVA for Case IV: Serial Between Manufacturing Cells –Serial within Manufacturing Cells Structure (dependent variable: efficiency [output/worker])

Source	d.f	SS	MS	F	Pr > F
Between-Cell Heterogeneity (BH)	1	373.38	373.38	372.27	0.000 **
System Size (SS)	1	317.33	317.33	316.38	0.000 **
Cells Size (CS)	1	330.53	330.53	329.55	0.000 **
Knowledge Transfer (KT)	1	116.15	116.15	115.80	0.000 **
BH*SS	1	0.06	0.06	0.06	0.807
BH*CS	1	0.11	0.11	0.11	0.738
BH*KT	1	19.81	19.81	19.75	0.000**
SS*CS	1	3.79	3.79	3.78	0.052**
SS*KT	1	0.17	0.17	0.16	0.685
CS*KT	1	5.34	5.34	5.33	0.021**
Error	1589	1593.75	1.00		
Total	1599				

[Weighted Least Squares ANOVA with a significance level of 5%; R-Sq (Adj) = 43.06%; Box Cox Transformation with λ=0.37]

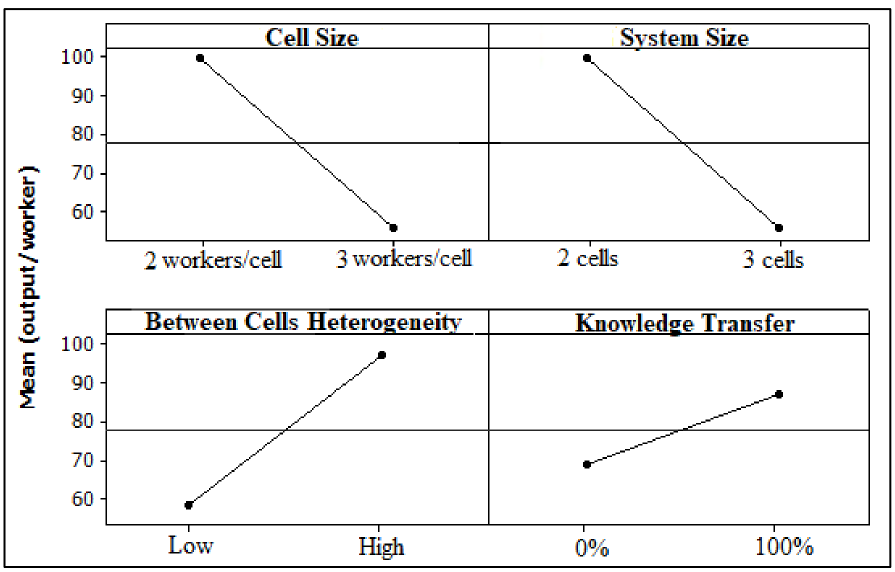

Figure 2.12. Main Effects Plot for Case IV. Serial Between Manufacturing Cells – Serial Within Manufacturing Cells.

For the Knowledge Transfer-Between-Cell Heterogeneity interaction, for both scenarios of between-cell heterogeneity, the consideration of knowledge transfer resulted in a significantly higher system efficiency than the scenarios that did not consider the knowledge transfer between workers. These results suggest that for both homogeneous and heterogeneous cellular systems defined with a pure serial manufacturing configuration, the consideration of knowledge transfer between workers is meaningful. Similar results were obtained for the Knowledge Transfer-Cell Size interaction, where for both cases of Cell Size, the system efficiency was significantly different between scenarios that considered the effect of knowledge transfer between workers and scenarios that did not consider it (*t*-test, $p = 0.000$). In both cases a higher efficiency was obtained when the Knowledge Transfer was considered as part of the assignment of workers for both cases of Cell Size.

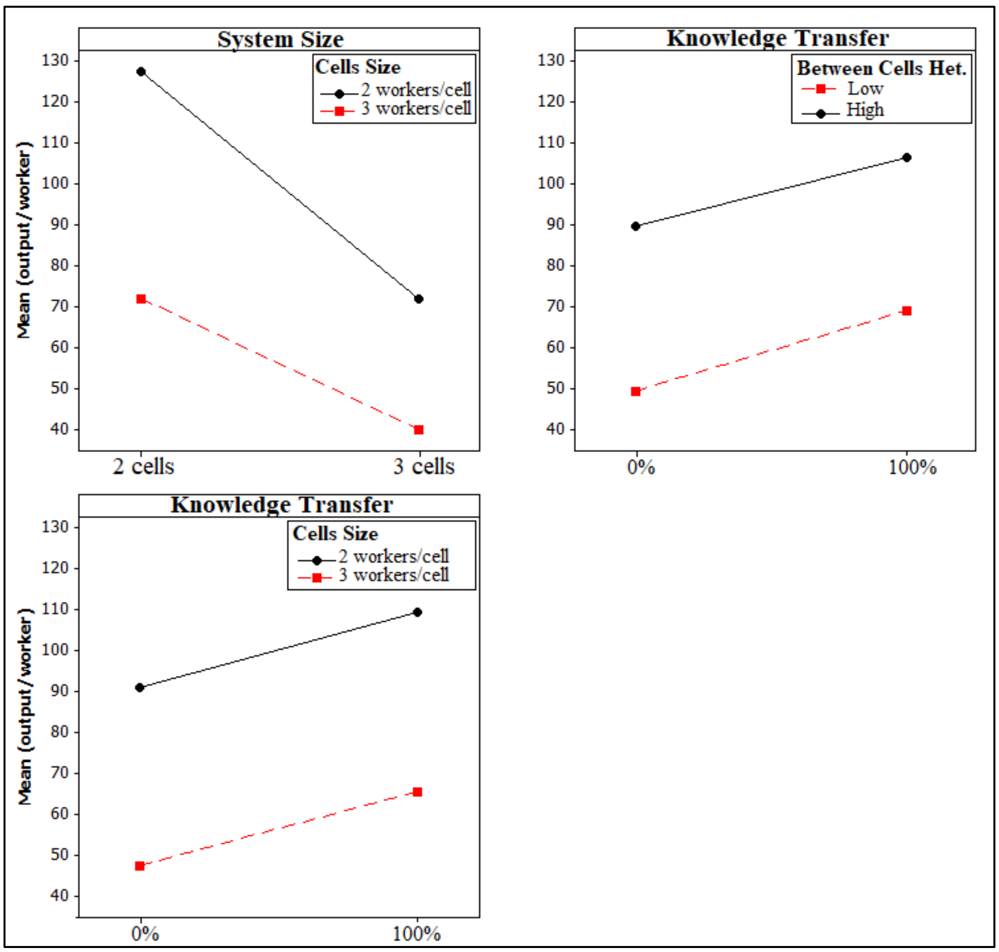

Figure 2.13. Interaction Plot for Case IV. Serial Between Manufacturing Cells – Serial Within Manufacturing Cells.

2.5 Conclusions and Managerial Implications

The results from this exploratory effort contrast across the four cases investigated, where there were significant effects of several organizational factors, such as system size, cell size, between-cell heterogeneity, and the consideration of knowledge transfer, on system performance. Workforce heterogeneity was considered through the estimation of individual worker productivity as a function of the cumulative experience on the task and the individual capacity of learning by doing and by knowledge transfer, as proposed in Nembhard and Bentefouet (2015). A contribution of the current study is the demonstration of the value of considering these factors as part of workforce planning process in a cellular manufacturing setting. It should be noted that the literature related to the consideration of these factors as part of workforce planning models is scarce in general, and absent with respect to cellular manufacturing settings in particular.

Four main research questions were investigated in this work: (i) How does the consideration of knowledge transfer for the worker-cell assignment impact system efficiency in different production system structures? (ii) How does the consideration of between-cell heterogeneity in addition to workforce heterogeneity impact production system efficiency? (iii) What is the effect of system configuration dimensionality on system efficiency, where system dimensionality is a function of cell size and the number of cells in the production system? (iv) What are the relative impacts of the worker-cell assignment, considering factors of knowledge transfer, between-cell heterogeneity, cell size, and the number of cells in the production system?

The simulations performed for this study considered four different cellular manufacturing configurations. From this, we note a number of similarities, as well as some contrasting results. We organize these broad findings into four areas below:

1. In all four system configurations, knowledge transfer had a significant positive effect on system efficiency, highlighting the importance of its consideration as part of a workforce planning strategy. In Nembhard and Bentefouet (2015), the concept of knowledge transfer was defined as the ability of individuals to use knowledge from within a team to improve individual performance. From a managerial perspective, these

results suggest the consideration of team composition of new workers in a specific task with more experienced workers with higher level of knowledge, to benefit from the effect of knowledge transfer between workers and hasten the learning process of the new worker in the task. Similarly, the impact of knowledge transfer on serial system efficiency depended on cell size and between-cell heterogeneity. For this case, the difference was greater for a smaller cell size and high heterogeneity scenario. These results suggest that for a serial manufacturing configuration defined with a pure serial structure, the consideration of knowledge transfer is particularly important for systems composed of smaller cell teams and systems with higher levels of between-cell heterogeneity.

2. Between-Cell Heterogeneity (BH) showed a significant effect on system efficiency, consistently with the highest level of between-cell heterogeneity resulting in the highest system efficiency. This was consistent in almost all configurations, except for the case with a serial configuration between manufacturing cells and a parallel structure within the cells. These results highlight the impact of the consideration of between-cell heterogeneity as part of workforce planning methods. We note that not considering the heterogeneity between cells as part of the worker-cell assignment, could affect the accuracy of production estimates, and subsequently system performance. The results of the current study as pertaining to between-cell heterogeneity, are consistent with the earlier findings (e.g., Shafer et al. 2001) where we found that higher levels of workforce heterogeneity in a system defined with independent tasks resulted in higher system productivity. Shafer et al. (2001) suggest that these results are obtained because for heterogeneous workers, the faster workers more than make-up for deficits from the slower workers.

For the serial cases, the results concerning between-cell heterogeneity may be explained by the heterogeneity of workers' skills. In the current study, the workers' population was generated assuming that in low heterogeneity scenarios, a worker will have the same learning parameters, which determine the individual potential productivity for all tasks, because all tasks have the same complexity. For the scenarios with high levels of between-cell heterogeneity, the workers' profiles were generated and scaled by the complexity of the cells. This means that a worker has different learning parameters for different tasks depending on their complexity, and as consequence a different task performance depending of the complexity of the cell. As a result, the pool of available skills or workers' potential productivity is more diverse, allowing workers to be assigned so as to help deal with the system bottleneck.

3. In changing from a pure parallel configuration to a system with serial components either between or within cells, the factors associated with the system dimensionality (SS & CS) became significant with respect to system efficiency. Prior studies of cellular system design have often ignored the effect of human variability on system performance (Javadi et al. 2013, Shiyas and Pillai 2014, Alhourani 2016, Jawahar and Subhaa 2017). Yet the results of the present study point to the impacts of physical system factors such as system dimensionality and system structure on system efficiency, when considering human variability as a function of individual learning and knowledge transfer. Specifically, for pure serial configurations within and between manufacturing cells, the results suggest that the consideration of the system dimensionality, defined as the number of workers per cell and the total number of cells in the system, is particularly important when human variability is considered as part of system performance. Freiheit et al. (2004) investigated the effect of system configuration on system productivity, pointing out the benefits of parallel connections with crossover in serial-parallel configurations. Similarly, Freiheit et al. (2007) examined the effect of system configurations considering the labor requirements for production. The study demonstrated the benefit of parallel configurations from the standpoint of annual cost saving in labor, in reduction in production variability, and as well from the perspective of increase in reliability. These studies consider the effect of system structure on system performance, but do not extend the study to the analysis of system dimensionality variation and the consideration of human variability. Dode et al. (2016) address the problem of production system design based on productivity. The study considered the effect of human variability on system productivity through the modeling of human fatigue and learning capacity of workers. However, the study does not extend to the analysis of the effect of system configuration structure on system productivity. The results of the present study contribute to addressing this gap.

4. Systems with fewer cells were more efficient than larger configurations. For systems with serial elements, there was a loss in efficiency as a result of a differential in system balance. The smaller serial cells were more efficient than the larger serial cells, in part because the larger cells involve a longer serial chain, which constrains productivity to a degree. Some of the challenges that have been discussed in the literature for serial structures include: loss in reliability, loss in flexibility, and loss in balance (Bellgran and Säfsten 2010, Grzechca 2014). In contrast, for a system that is serial among cells and parallel within the cells, the larger cells were more efficient. This suggests that larger systems, in terms of number of cells, can be associated with the lowest average production rate per worker, which may open future areas of research and consideration in the field of system design in manufacturing environments.

The consideration of the main results of the present study will serve future research focused on the development of methods to address the worker-cell assignment. The study of within- cell heterogeneity on the worker cell assignment and their effect on the system performance is of interest for future work. The present study will inform future research on the development of methods for cellular manufacturing design considering both, physical system factors and human factors such as individual learning capacity and the effect of knowledge transfer between workers. In the current study, the exploration of system dimensionality, in terms of both cell size and system size, was constrained by current combinatorial computation limitations. We note that the current results involve exact optimal assignments and schedules. While larger systems are also of interest, the inclusion of potentially suboptimal decisions, solution quality can confound associated results, which will be a challenge for future researchers. Similarly, the current results are limited to the four system structures presented in the current study. Future exploration of larger and more complex hybrid structures between and within manufacturing cells would be of interest in order to extend the results of the current study. Questions related to the effect of other factors such as within-cell heterogeneity, demand variation, absenteeism, or individual losses given fatigue, team coordination, or forgetting effect remain open and would be of interest for future studies.

Appendix 2-A. Genetic Algorithm for Solving the Worker-Cell Assignment Problem.

A genetic algorithm (GA) was implemented for solving the worker-cell assignment problem when simulation exceeds 72 hours of computational time for obtaining the optimal solution. The GA was coded considering generating 30% of the offspring using 3-point crossover, 30% using 1-point crossover, and 40% using mutation. Each gene of the chromosomes represents a worker-task assignment. The method was implemented considering 50 iterations in the fashion described below.

Initially, the GA started with an initial population of size 10, which each unit of the population is called a chromosome and correspond to feasible worker-cell assignment. The 10 chromosomes were evaluated based on system efficiency as objective function, considering a maximization objective. The top 30% chromosomes, that means the three chromosomes of our population that have the best values of the performance measure, were selected as primary chromosomes for the crossover operation for the generation of the offspring or new population. The crossover was performed taking the primary chromosome and secondary chromosome that was randomly selected for the next best 50% of the population (the 5 chromosomes that follows in highest values of the objective function) (Figure 2-A1). The swap points of the primary chromosome were randomly selected, 1 swap point for 1-point crossover and 3 swap points for 3-points crossover, wherein the value of the primary chromosome is swap with the value of the secondary chromosome.

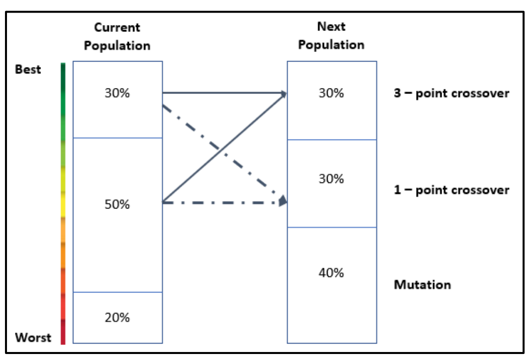

Figure 2-A1. Structure of the GA for Solving the Worker-Cell Assignment Problem.

The second operation performed for the generation of the new offspring is the mutation. In this work we implemented 1-point mutation. For the 1-point mutation a chromosome from the original population was randomly selected, selecting a gene of this chromosome randomly as well. This gene is substitute then by a new gene generated randomly from a uniform distribution. Only one perturbation of the selected chromosome is made. objective function previously described. Finally, the offspring was compared with the old population, and When the offspring was generated, it was evaluated based on the selected the 10 incumbent chromosomes were selected. The method iterated through this process of offspring generation and comparison for a total of 50 iterations. The setup of the parameters of the GA was carried out comparing the performance of the algorithm across smaller instances of the problem where the optimal solution was known.

Genetic Algorithm (GA)

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(1) Generate an initial population composed of 10 chromosomes

(2) Evaluate Population, Objective function = System Efficiency.

(3) Rank the chromosomes based on the objective function value (maximize)

(4) Generate the offspring.

> a. The best 30% of the population is used to generate new spring through crossover. This going to be used as the primary chromosome. The secondary chromosome to do crossover is randomly selected for the follow 50% of the best chromosomes of the population. Through this process is generated 30% of the new population or offspring through 3-point crossover and 30% of the offspring using 1-point crossover.
>
> b. Generate 40% of the population through mutation in one point. A small perturbation is added to a chromosome randomly selected from the population. One of the workers change its assigned task.

(5) Evaluate the offspring

(6) Compare the chromosomes of the old population and the offspring based on the objective function.

(7) Select the 10 incumbent chromosomes.

(8) Repeat steps 3 to 7 until the method reach 50 iterations.

CHAPTER 3

Workforce Management in Team Sizing: Knowledge Transfer and Process Loss Effect on Team Performance.

Abstract

This study explores the effect of team size on team performance in an experiential learning environment considering knowledge transfer and process loss simultaneously. Many organizations have considered implementing teamwork as an approach to improve organizational capacity, meet customer needs, and boost the learning process of novice workers. However, despite the benefits offered by teamwork, the literature has also shown negative aspects of this kind of work setting, including process loss. Studies have suggested the effect of process loss and knowledge transfer as a function of team size. Specifically, larger teams have more available human resources and available knowledge than smaller teams. However, larger teams are correlated with productivity losses due to the additional effort required from individuals to coordinate and communicate with other team members to efficiently perform tasks. Questions related to the design and implementation of teamwork in organizations, such as the determination of optimal team size and grouping of workers, have become increasingly relevant. Most literature related to teamwork focuses on exploring the factors that cause process loss or knowledge transfer separately. The impact of process loss and knowledge transfer on team performance and its effect on team formation remains unsettled. The current study brings these elements together to investigate the joint effects of knowledge transfer and the process loss on team performance resulting from the incorporation of additional workers into the work team. Managerial implications are derived to help organizations make decisions about the design and application of team-based work strategies in different organizational settings.

3.1 Introduction

The implementation of work teams is a common and attractive strategy for managers across academic, manufacturing and service organizations. The implementation of work teams in organizations has been linked to many benefits including but not limited to workload division, learning from knowledge sharing, foundation of a collaborative environment, amplification of individual perspective, and incrementing of organizational expertise (Cross 2000; Drach-Zahavy and Somech 2002; Baeten & Simons 2014). Recently, attention has been paid specifically to the process of knowledge transfer between workers at team and organizational levels (Hendricks 1996; Reagans et al. 2005; Knockaert et al. 2011; Baeten & Simons 2014; Glock & Jaber 2014; Nembhard & Bentefouet 2015; Jin et al. 2018). The process of knowledge transfer allows individuals to use this knowledge accumulated by other team members in order to improve their individual performance. (Reagans et al. 2005; Nembhard & Bentefouet 2015).

However, despite the benefits associated with the implementation of work teams and the effect of knowledge transfer between workers within teams, literature has also shown some negative consequences within team-based work settings, such as process loss (Steiner 1972; Erez and Somech 1996; Mueller 2012; Staats et al. 2012; Peltokorpi and Niemi 2018). Team process loss occurs when the team's actual performance falls below the team's potential performance as a consequence of factors including coordination, motivation and relational processes between members (Steiner 1972; Mueller 2012; Staats et al. 2012; Peltokorpi and Niemi 2018). Thus, the actual performance as a team is lower than the sum of the individual performance capacity of the team members (Steiner 1972). Extensive research has been dedicated to exploring the different factors affecting team performance (Erez and Somech 1996; DeMatteo et al. 1998; Drach-Zahavy and Somech 2002; Doolen et al. 2003; Ogot & Okudan 2006; Mueller 2012; Jaca and Viles 2013; Peters and Carr 2013; Peltokorpi and Niemi 2018), recognizing that the effect of each factor varies depending on the type of task and the work setting in which the teamwork system is applied (Steiner 1972; Doolen et al. 2003; Ogot & Okudan 2006; Jaca and Viles 2013). Consequently, studying the design of teamwork has become vital in order to 1) understand the factors that affect team performance in a given work setting and 2) look for strategies that support team design that allows organizations maximize the advantages obtained from a teamwork strategy implementation.

This study explores team performance as a function of process loss and knowledge transfer between workers in an experiential learning environment. Most existing literature related to work teams focuses on exploring factors that cause process loss or knowledge transfer individually. The joint impacts of process loss and knowledge transfer on team performance is not clear when considering a teamwork strategy in an experiential learning environment. The current study brings these competing aspects together to investigate the interactions of knowledge transfer and process loss on team performance resulting from the incorporation of an additional worker into the work team. The study is developed through a series of simulations considering a single team-based work setting and four controllable experimental factors: degree of process loss, degree of knowledge transfer, workforce heterogeneity, and the team size. Research has linked the effect of process loss and knowledge transfer as a function of the number of workers in the team (Thomas & Fink 1963; Steiner 1972; DeMatteo et al. 1998; Mueller 2012; Nosenzo et al. 2015; Peltokorpi and Niemi 2018). Similarly, literature related to teamwork has highlighted the effect of workforce heterogeneity as significant on team performance (Steiner 1972; DeMatteo et al. 1998; Drach-Zahavy and Somech 2001; Shafer et al. 2001; Hamilton et al. 2003; Peeters et al. 2006; Jaca et al. 2013).

The following research questions are addressed through this work as the main objective of the study: (1) How does optimal team size change for different levels of a) workforce heterogeneity, b) process loss, and c) knowledge transfer in conjunctive, disjunctive and additive tasks? and (2) What team sizes are best across different levels of Knowledge Transfer and Process Loss? The main contribution of this work is an explication of the joint impact of knowledge transfer and process loss on team performance resulting from the incorporation of an additional worker into the team and to provide insight to guide managers in making decisions about team size selection as part of the team design process. The remainder of the manuscript is organized as follows: Section 3.2 presents a review of the literature related to i) the relation of process loss, knowledge transfer, and team size on team performance ii) the existing methods of team formation that considers these factors. Section 3.3 describes the simulation setting used in this study, as well as the implemented experimental design. In Section 3.4, a discussion of the most relevant results is presented. Finally, the conclusion and further research directions are discussed in Section 3.5.

3.2 Literature Review

Teamwork in organizations has been linked in the literature to several benefits. In particular, the possibility of collaboration between individuals and the availability of resources to perform a specific task have been commonly highlighted as benefits of the implementation of teamwork. Previous studies have argued that the implementation of teamwork in organizations provides individuals with the opportunity to collaborate and learn from one another, helping to attain better task performance as a team (Cohen & Levesque 1991; Esteban & Ray 2001; Doolen et al. 2003; Tohidi & Tarokh 2006; Akinola & Ayinla 2014), as well as improving the individual performance of team members (Reagans et al. 2005; Destré et al. 2008; Davies 2009; Nembhard & Bentefouet 2015; Jin et al. 2018). Although teamwork settings offer significant benefits, previous research has also recognized challenges posed in these settings that cause teams to perform under their potential capacity (Steiner 1972; Esteban & Ray 2001; Peltokorpi & Niemi 2018). This phenomenon has been extensively studied and is known within literature as process loss (Steiner 1972; Mueller 2012; Halpin & Bergner 2018; Peltokorpi & Niemi 2018). Previous studies have pointed to team size as one factor with a significant impact on the benefits obtained from implementing a teamwork strategy but also on the losses incurred. The number of members in a team is related to the actual capacity the team possesses to perform a task but also to the amount of coordination the team must have, the loss of motivation individuals would face, and the relational links members should try to establish in order to effectively perform a task (Steiner 1972; Mueller 2012; Peltokorpi & Niemi 2018). These arguments have been the basis of several studies on teamwork aiming to determine the optimal team size in order to maximize the benefits of implementing a teamwork strategy and minimize the effects associated with process loss (Thomas & Fink 1963;

Manners 1975; Kameda et al. 1992; Tohidi & Tarokh 2006; Liang et al. 2008; Akinola & Ayinla 2014; Mao et al. 2016).

Despite the efforts of many studies to explore the benefits and costs of teamwork implementation and how those factors relate to team size, the extension of this knowledge to the formulation of mathematical models that address team formation incorporating the team size benefit-cost tradeoff is scarce. Specifically, mathematical models have not been previously developed to address the team formation problem considering the effect of learning from others simultaneously with the effect of process loss faced by teams as function of the team size

In Safizadeh (1991), a theoretical framework was presented to guide managers in the design of work teams within manufacturing environments. This work describes a theoretical model without a mathematical formulation to perform the grouping of workers considering factors such as individual skills, member synergy, and job types, which have been argued to affect team dynamics. In Asking and Huang (2001), a mathematical formulation was proposed to address worker team formation in a cellular manufacturing configuration. The model considers team dynamics from the perspective of synergy between individuals within the team. Wi et al. (2009) proposed a framework based on a genetic algorithm to address the team formation problem. The proposed method considers individual skills required by assigned task, as well as information about the social networks of each evaluated member, which is taken in the study as a representation of member familiarity. Stroieke et al. (2013) addressed the team formation problem for a production system setting, considering the workforce heterogeneity and the balance of workload as the objective function. The method uses a team formation index and individual learning curves to determine whether an individual is a good fit for a team based on the homogeneity of members' production rates within teams. Wi et al. (2015) presented a framework to address the formation of effective teams in the context of productive, creative, and learning-oriented tasks. The proposed framework uses a mathematical expression that returns a score value for users, in order to evaluate the team fit with respect to the levels of productivity, creativity, or learning capacity. Faraset et al. (2016) proposed a framework to address the team formation problem that quantitatively accounts for workers' social interaction.

The framework incorporates network theory and a heuristic approach to addressing the problem. None of these models discussed above account for the effects of process loss, knowledge transfer, or team size on the team performance as part of the team formation approach.

Glock and Jaber (2014) conducted the first study to propose a mathematical model accounting for the effects of team size and learning from others within teams based on team productivity. The model considers team member dynamics and the effect of team size through the incorporation of the concepts of “motivation/ability of individuals to share and absorb knowledge” from others within the team and “factor regulating the time delay in transfer of knowledge due to group size for individuals,” respectively. This model accounts for the effect of team size by assuming that team size affects the speed at which the transfer of knowledge happens between team members. Although the model considers the effect of group size on team performance, it assumes that as time increases, the effect of group size on team performance decreases and approaching zero. However, this assumption would not necessarily be met in all cases of work teams. Although some process loss can be overcome through the repetition of working together as a team on a specific task, given improvement of coordination and familiarity processes (Peltokorpi & Niemi 2018), other aspects of process loss, such as individual motivation caused by individual members’ perception of rewards/recognition and support, are not necessarily overcome in this way.

Nembhard and Bentefouet (2015) addressed the team formation problem as part of the worker-assignment problem, considering worker interaction through the modeling of team size and learning by knowledge transfer. The study proposed a mathematical model that relates the effect of worker interaction to the individual productivity through the concept of learning by knowledge transfer. The authors showed the significance of considering the workers’ interaction as part of the worker assignment problem and proposed a heuristic approach to address the formation of teams. The study focused specifically on pure serial and parallel manufacturing structures and thus did not account for the effect of process loss as part of the team dynamic and team size.

Peltokorpi and Niemi (2018) proposed a mathematical model that accounts for the effect of workers' interaction within a team on team performance. As part of the estimation of team productivity, the model considers the effect of process loss as a function of team size, wherein as team size increases, the process loss faced by work teams also increases. Similarly, the study argues that as a task is repeated, the process loss experienced by the work team decreases. The study considered a limited number of task repetitions and replications, and no conclusion was reached regarding the impact of process loss on team performance when the team productivity reaches a steady state. The model the study proposed to estimate the team productivity does not account for either individual contribution to the team or the effect of process loss on the individual productivity of team members. Another limitation of the proposed model is that it does not account for the effect on team performance of knowledge transfer between workers in a team.

3.3 Methodology

The team formation problem is addressed in this work considering heterogeneous workers and an experiential learning environment. The study was performed through a simulation experiment exploring the effects of multiple experimental factors including the degree of process loss, degree of knowledge transfer, workforce heterogeneity, and team size on team performance. Team performance is defined as team productivity, measured in output/worker units. The simulations and data used for the study are described below.

Simulation Scenario:

The simulations in this study were constructed using MATLAB™ considering a production system of a single repetitive task over a time horizon of 50-time periods. Three different cases of task type were evaluated in this work: Case I. conjunctive task, Case II. disjunctive task, and Case III. additive task. The simulation for Case I. consisted of a conjunctive task setting, defined as a task in which every member in the team needs to develop a part of the task in order to achieve the task's completion. For example, a conjunctive task can be found in production environments where the assembly of a final product is divided into elements and each element is assigned to a team member. In this scenario, all elements of the assembly task need to be completed in order to obtain a finished product. The performance of the team in a conjunctive task setting is determined by the least competent member (Steiner 1972). Case II. represents a system consisting of a disjunctive task. Disjunctive tasks represent indivisible tasks where the team needs to complete the task together as a single problem. A disjunctive task can be found in settings where projects that are assigned as a single-indivisible unit needs to be completed by a team. For example, software coding projects or brainstorming for problem solving are often disjunctive, and the performance of the team depends on the most competent worker in the team (Steiner 1972). Case III. represents a system composed of an additive task, defined as a task where the individual contributions of the team members are combined as a single output. An example of an additive task in industrial settings can be a parallel production structure, where a team of workers work together by each completing the same operation independently. Thus, the team performance is determined by the sum of the individual contributions of all team members (Steiner 1972).

We use a full factorial experimental design with four factors as summarized in Table 3.1. The explored factors include: Team Size (TS) at six levels, Workforce Heterogeneity (WH) at three levels, Degree of Knowledge Transfer (KT) at five levels, and Degree of Process Loss (PL) at five levels (Table 3.1). A total of 450 experimental runs were evaluated for each of the task type cases, considering 50 replications for each experimental treatment.

For the Team Size (TS) factor, six levels were considered corresponding to one worker per task, through a six-worker team. The workforce selection for this factor was dependent across the different levels of team size. That is, we treat each additional worker as a marginal increment from the smaller team instance. For example, when TS=3, two of the workers are the same as the two workers from TS=2. This has the effect of reducing the variance between cases, since we are interested in what happens when we add or remove a member of the team. The specific workers selections are random. The objective of this type of sampling across the increase of team size is to evaluate whether the incorporation of an additional worker into the work team is beneficial for the specific task, considering the effect of knowledge transfer and process loss on the team performance.

Table 3.1. Experimental Design.

Factors	Levels
TS: Team Size (workers/team)	1, 2, 3, 4, 5, 6
WH: Workforce Heterogeneity (%)	50, 100, 150
θ: Degree of Knowledge Transfer (%)	0, 25, 50, 75, 100
δ: Degree of Process Loss (%)	0, 25, 50, 75, 100

The second factor investigated as part of the study was Workforce Heterogeneity (WH). Three experimental levels were considered for this factor (Table 3.1), defining the workforce heterogeneity factor with respect to the individual learning parameters. In this study, the workforce heterogeneity was considered by scaling the variance-covariance matrix associated with the probability distribution of the parameters used to construct the workers' profiles (Nembhard & Shafer 2008). The variance-covariance matrix provided in Nembhard and Shafer (2008) was used as a basis, representing the case of WH = 1. For the cases of WH = 0.5 and 1.5, the variance-covariance matrix used for the case of WH = 1 was scaled by a factor of 0.5 and 1.5, respectively. The main objective of the examination of the WH factor was to investigate the impact of workforce heterogeneity, with respect to the individual learning parameters, on team performance for different task types and different scenarios of process loss and knowledge transfer.

Lastly, the third and fourth factors evaluated as part of this study were the Degree of Knowledge Transfer (θ) and the Degree of Process Loss (δ). For the examination of these factors, five experimental levels were considered for each one. For the factor of Degree of Knowledge Transfer, the first level evaluated corresponds to the case where no knowledge transfer between workers occurs, θ=0. This means that workers cannot benefit from the experience of other members in the team. The second level evaluated for this factor, θ=0.25, is the case in which a worker uses 25% of the experience of other members in the team to improve its individual performance. The third, fourth, and fifth levels examined in this factor correspond to θ=0.50, θ=0.75, and θ=1, respectively, and follow the same logic, where a worker uses 50% (θ=0.50), 75% (θ=0.75), or 100% (θ=1) of the experience of other members in the team to improve its individual performance.

For the factor of Process Loss (δ), the first level evaluated corresponds to δ =0, which represents the case in which no Process Loss occurs in the team. This case is the best scenario in terms of team productivity, representing the case where the team reaches its full potential. The second level of this factor corresponds to the case of δ=0.25, meaning that the actual team productivity is 25% below its potential and 75% above the worst scenario of team productivity. For the third level of this factor, δ=0.50, the actual team productivity is 50% below its potential productivity and 50% above the worst scenario of team productivity. The fourth and fifth levels, which correspond to δ=0.75 and δ=1, respectively, follow the same structure. The Process Loss is then calculated by comparing the team actual productivity with the team potential productivity. The main objective of the examination of these factors was to investigate the impact of the degree of knowledge transfer and process loss on the team performance, and consequently how it affects the selection of team size for different task types.

Workers' Production Rate Simulation:

The estimation of the individual worker performance in this work considered the effects of knowledge transfer and process loss as a result of the team context. For this, a modification of the mathematical model described in Equation (3.1) was considered (Nembhard & Bentefouet 2015).

$$y_x = k * \left(\frac{\theta * T + x + p}{\theta * T + x + p + r}\right) \tag{3.1}$$

This model estimates the worker production rate, Y_x, considering the worker's previous experience, represented by the parameter p, the amount of cumulative work x in a specific task, the steady state level k that will be achieved when the worker completes the learning process, and the cumulative production required to achieve a k/2 level of performance, represented by the parameter r. The parameter θ and the variable T correspond to the percentage of knowledge transferred from other workers performing similar tasks and the total cumulative knowledge of other workers, respectively.

The mathematical model presented in Equation (3.1) as proposed in Nembhard and Bentefouet (2015) incorporates the effects of learning by doing and learning by knowledge transfer in the estimation of the individual worker performance. Research has shown that in team contexts, the individual performance can benefit from the available human resources and available knowledge in the team (Thomas & Fink 1963; Reagans et al. 2005; Mueller 2012). However, individual performance can also be negatively impacted as a result of coordination, relational, and motivational processes between team members (Steiner 1972; Erez and Somech 1996; Mueller 2012; Staats et al. 2012; Nosenzo et al. 2015; Peltokorpi & Niemi 2018). The loss in productivity resulting from these coordination, relational, and motivational processes between team members is known as process loss, and its impact changes according to different organizational settings, task types, and team sizes (Thomas & Fink 1963; Steiner 1972; DeMatteo et al. 1998; Doolen et al. 2003; Ogot & Okudan 2006; Mueller 2012; Jaca & Viles 2013; Nosenzo et al. 2015; Peltokorpi & Niemi 2018). Literature related to teamwork and process loss lacks a mathematical model that considers the effect of process loss on the estimation of individual productivity. This work aims to study the interaction between the process loss effect resulting from the increase in required coordination, relational, and motivational processes due to the incorporation of an additional member to the team, and the knowledge transfer effect resulting from the increase in available human resources and available knowledge in the team, for team performance. For this, we employ a modification of Equation (3.1) in Equation (3.2) in order to also consider the effects of process loss in the performance estimation.

$$y_x = (1 - L)\delta k\left(\frac{x+p+\theta T}{x+p+r+\theta T}\right) \tag{3.2}$$

The effect of process loss is represented in Equation (3.2) by parameter L, which quantifies the percentage of individual productivity that is lost from the need for required coordination, the need to build relationships and communication links with other individuals in a team, and the loss of motivation that results from working in a team context of a specific size. The parameter L is bounded by 0 and 1. The model assumes a constant level for a given team size.

Input Data for the Simulation Experiment:

Each worker profile consists of a set of learning parameters (k, p, r) for each different task. Nembhard and Bentefouet (2015) describe the process for model parameter (*k*, *p*, r) estimation. An empirical dataset of 75 workers (Shafer et al., 2001). Through the fitting process, they modeled the parameters associated with Equation 3.1 (k, p, r) using a Multivariate Normal Distribution (MVND) with a mean and standard deviation presented in Table 3.2 (Nembhard & Shafer 2008). For the current study, the sampling of the parameters for the construction of the workers' profiles was based on a MVND, using as an input the mean presented in Table 3.2 and the variance-covariance matrix presented in Table 3.3. The variance-covariance matrix used for the sampling in this work was determined based on the level of the factor Workforce Heterogeneity (WH) for each specific experimental treatment.

Table 3.2. Mean and Variance–Covariance Matrix associated with the Estimation of the Learning Parameters (Nembhard & Shafer 2008).

$\mu = \begin{bmatrix} \ln \boldsymbol{k} \\ \ln \boldsymbol{p} \\ \ln \boldsymbol{r} \end{bmatrix} = \begin{bmatrix} 3.34 \\ 4.57 \\ 4.73 \end{bmatrix}$	$\sum = \begin{array}{rl} \begin{array}{r} \ln \boldsymbol{k} \\ \ln \boldsymbol{p} \\ \ln \boldsymbol{r} \end{array} & \begin{bmatrix} 0.730 & 0.341 & 0.336 \\ 0.341 & 7.830 & 3.420 \\ 0.336 & 3.420 & 4.020 \end{bmatrix} \\ & \begin{array}{ccc} \ln \boldsymbol{k} & \ln \boldsymbol{p} & \ln \boldsymbol{r} \end{array} \end{array}$

Table 3.3. Variance–Covariance Matrix for different levels of Workforce Heterogeneity.

WH = 0.5	**WH = 1**	**WH = 1.5**
$\Sigma = \begin{array}{rl} \begin{array}{r} \ln \boldsymbol{k} \\ \ln \boldsymbol{p} \\ \ln \boldsymbol{r} \end{array} & \begin{bmatrix} 0.037 & -0.352 & -0.357 \\ -0.352 & 7.137 & 2.727 \\ -0.676 & 2.272 & 3.327 \end{bmatrix} \\ & \begin{array}{ccc} \ln \boldsymbol{k} & \ln \boldsymbol{p} & \ln \boldsymbol{r} \end{array} \end{array}$	$\Sigma = \begin{array}{rl} \begin{array}{r} \ln \boldsymbol{k} \\ \ln \boldsymbol{p} \\ \ln \boldsymbol{r} \end{array} & \begin{bmatrix} 0.730 & 0.341 & 0.336 \\ 0.341 & 7.830 & 3.420 \\ 0.336 & 3.420 & 4.020 \end{bmatrix} \\ & \begin{array}{ccc} \ln \boldsymbol{k} & \ln \boldsymbol{p} & \ln \boldsymbol{r} \end{array} \end{array}$	$\Sigma = \begin{array}{rl} \begin{array}{r} \ln \boldsymbol{k} \\ \ln \boldsymbol{p} \\ \ln \boldsymbol{r} \end{array} & \begin{bmatrix} 1.135 & 0.746 & 0.741 \\ 0.746 & 8.235 & 3.825 \\ 0.422 & 3.825 & 4.425 \end{bmatrix} \\ & \begin{array}{ccc} \ln \boldsymbol{k} & \ln \boldsymbol{p} & \ln \boldsymbol{r} \end{array} \end{array}$

Estimation for the Process Loss:

Team process loss occurs when the team actual performance falls below the team potential performance as a consequence of coordination, motivation, and relational processes between members (Steiner 1972; Mueller 2012; Staats et al. 2012; Peltokorpi & Niemi 2018). Several levels of process loss are investigated using a parameter for process loss degree, δ. For each specific team size, the upper and lower bounds of team process loss were determined. The upper bound of team process loss represents the case where the team performs at its minimal productivity. This case is defined as the worst scenario of team actual productivity (TP_W) and is represented by $\delta = 1$ (Figure 3.1). The lower bound of team process loss represents the case when the team perform at its potential productivity. This case is defined as the best scenario of team productivity (TP_B) and takes place when the degree of δ is equal to 0 (Figure 3.1). The current study explored the effect of process loss for each team size, considering different levels of process loss ($\delta = 0, 0.25, 0.5, 0.75, 1$) and assuming that the actual team productivity is within the previously defined upper and lower bounds. Details about the calculation of the upper and lower bounds, as well as about the integration of δ to the determination of the team process loss, are presented below.

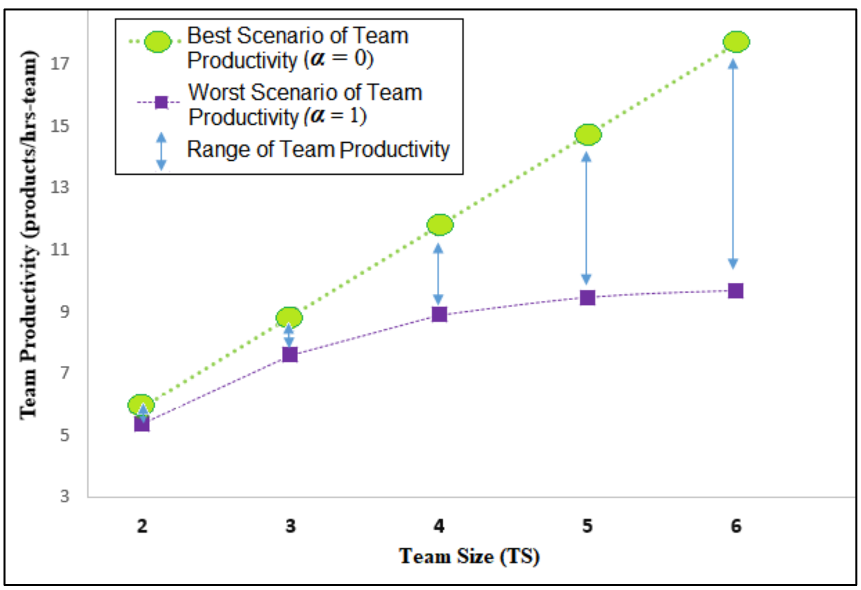

Figure 3.1. Range of Team Productivity by Group Size.

For the estimation of team productivity in the least productive scenario of process loss (δ =1) as a function of team size, the statistical data provided in Peltokorpi and Niemi (2018) was used. In Peltokorpi and Niemi (2018), an experimental study was carried out considering the group size and task repetition as controllable factors. The authors considered group sizes of 1, 2, 3 and 4 members per group and up to 4 repetitions of the task in order to investigate the effect of group size and repetition on the team process loss. We considered data provided in Peltokorpi and Niemi (2018) (Table 3.4) to fit the nonlinear model described in equation (3.3).

Table 3.4. Team Productivity (products/hour) in a Team Learning Context

Team Size	*Productivity*	*Productivity*
1	2.892	3.059
2	5.012	5.648
3	7.605	7.707
4	8.340	9.392

In equation (3.3), the dependent variable TP_W represents the team productivity, estimated as a function of the team size (TS). For the current study, equation (3.3) was assumed to represent the worst scenario of team actual productivity, with a mean square error and the p-value for the Lack of Fit Test of 0.15 and 0.8 respectively.

$$TP_W = 9.8358 * \left(\frac{e^{1.0367*TS}}{6.5823+e^{1.0367*TS}}\right) \tag{3.3}$$

The best scenario of team productivity is based on the potential productivity of the team, described as follows. For the estimation of the lower bound of team process loss, the "best scenario" of team productivity (TP_B), assumes zero process loss. To calculate team potential productivity, the productivity corresponding to an individual member is multiplied by the team size, based on the definition of team potential productivity which corresponds to the sum of the isolated individual productivity of team members (Steiner 1972). Then, the process loss percentage for each specific team size and level of $\boldsymbol{\delta}$ was obtained using equation (3.4).

$$L = \frac{TP_B - [(1-\delta)TP_B + \delta TP_W]}{TP_B} * 100 \tag{3.4}$$

3.4 Results and Discussion

This section presents the results and discussion for the three task type cases. The cases explored the effect of process loss and knowledge transfer as a function of team size on team performance, considering a system represented by I. a conjunctive, II. a disjunctive, and III. an additive task. The independent factors considered for the analysis were Team Size (TS), Workforce Heterogeneity (WH), degree of Knowledge Transfer (KT), and the degree of Process Loss (PL). A General Linear Model ANOVA with main effects and second order interactions was considered for each case to compare the effects of the experimental factors. Specifically, a Weighted Least Squares ANOVA was used to avoid heteroscedasticity in the residuals. Below, a discussion of the simulation results is presented.

The first case represents a production system composed of a single conjunctive task. The results of the ANOVA for this case are presented in Table 3.5. For this analysis, the minimum value of workers' output was considered as the dependent variable, given that for conjunctive tasks the productivity of the group is determined by the member who perform least well. In this case, the factors of Team Size, Workforce Heterogeneity, degree of Knowledge Transfer, and degree of Process Loss showed a significant effect on the considered performance measure at a confidence level of 95%. Similarly, all the second order interactions regarding these factors proved significant.

Table 3.5. ANOVA for Case I: Production System Composed of a Conjunctive Task.

Source	d.f.	SS (Adj)	MS (Adj)	F	Pr > F
Team Size (TS)	5	40146.5	8029.3	7949.4	0.00
Workforce Heterogeneity (WH)	2	541.1	270.5	267.9	0.00
Knowledge Transfer (KT)	4	15957.8	3989.5	3949.8	0.00
Process Loss (PL)	4	69374.6	17343.6	17171.1	0.00
TS*WH	10	221.6	22.2	21.9	0.00
TS* KT	20	4088.8	204.4	202.4	0.00
TS* PL	20	82366.2	4118.3	4077.4	0.00
WH* KT	8	79.0	9.9	9.78	0.00
WH* PL	8	41.1	5.1	5.09	0.00
KT * PL	16	388.7	24.3	24.05	0.00
Error	22402	22627.0	1.0		
Total	22499				

[Weighted Least Squares ANOVA with a significance level of 5%; R-Sq (Adj) = 96.7%]

The second case considered in this work represents a production system composed of a single disjunctive task. The system output considered as the dependent variable for the ANOVA was the maximum value of workers' output, given that for disjunctive tasks the productivity of the group is determined by the most competent member in the group. Similar to the conjunctive case, in this case, the main effect and second order interactions of the considered factors—Team Size, Workforce Heterogeneity, degree of Knowledge Transfer, and the degree of Process Loss—showed a significant effect on the considered performance measure at a confidence level of 95% (Table 3.6).

Table 3.6. ANOVA for Case II: Production System Composed of a Disjunctive Task.

Source	d.f.	SS (Adj)	MS (Adj)	F	Pr > F
Team Size (TS)	5	32220.0	6444.0	6158.9	0.00
Workforce Heterogeneity (WH)	2	653.8	326.9	312.4	0.00
Knowledge Transfer (KT)	4	14344.1	3586.0	3427.4	0.00
Process Loss (PL)	4	61929.3	15482.3	14797.4	0.00
TS*WH	10	308.9	30.9	29.5	0.00
TS* KT	20	6644.6	332.2	317.5	0.00
TS* PL	20	71602.7	3580	3421.8	0.00
WH* KT	8	18.8	2.3	2.24	0.02
WH* PL	8	189.5	23.7	22.6	0.00
KT * PL	16	637.5	39.8	38.1	0.00
Error	22402	23438.9	1.0		
Total	22499				

[Weighted Least Squares ANOVA with a significance level of 5%; R-Sq (Adj) = 96.3%]

The third case considered was a production system composed of a single additive task. The results of the ANOVA for this case are presented in Table 3.7. For this analysis, the average output per worker was considered as the dependent variable for the analysis. Within this kind of system, the output represents the sum of the output of the individual contributions of team members. In this case, the selection of the average output per worker as the performance measure for the ANOVA analysis corrects for the scaling of different system sizes explored as part of the factor of Team Size, such that the comparison between systems of different dimensions is relatable. The results of the ANOVA for this case showed that the factors of Team Size, Workforce Heterogeneity, degree of Knowledge Transfer, and the degree of Process Loss had a significant effect on the considered performance measure at a confidence level of 95%. All the second order interactions resulted in a significant effect on the performance measure in this case.

Table 3.7. ANOVA for Case III: Production System Composed of an Additive Task.

Source	d.f.	SS (Adj)	MS (Adj)	F	Pr > F
Team Size (TS)	5	72224.2	14444.8	14127.2	0.00
Workforce Heterogeneity (WH)	2	105.1	52.6	51.4	0.00
Knowledge Transfer (KT)	4	22612.1	5653.0	5528.7	0.00
Process Loss (PL)	4	94004.3	23501.1	22984.4	0.00
TS*WH	10	125.8	12.6	12.3	0.00
TS* KT	20	4773.0	238.7	233.4	0.00
TS* PL	20	102606.3	5130.3	5017.5	0.00
WH* KT	8	40.2	5.0	4.9	0.00
WH* PL	8	89.9	11.2	11.0	0.00
KT * PL	16	382.4	23.9	23.4	0.00
Error	22402	22905.6	1.0		
Total	22499				

[Weighted Least Squares ANOVA with a significance level of 5%; R-Sq (Adj) = 97.3%]

Team Size:

For the factor of Team Size, the results showed that for all three cases—conjunctive, disjunctive, and additive single tasks—a significant difference in system performance was obtained when considering different team sizes as part of the team design process (Table 3.5, Table 3.6, Table 3.7). To compare the significance of the differences in the system performance means for the different levels of the factor of Team Size, a multiple comparison test was performed for each case using a Tukey method with a statistical confidence level of 95%. The results of the multiple comparison test revealed that all the levels investigated for the factor of Team Size (TS = 1, 2, 3, 4, 5, or 6 workers/team) resulted in a significant difference in system performance for each of the three task types (Table 3.8). These results indicate that the selection of team size as part of the team design process would significantly impact the team performance when a conjunctive, disjunctive, or additive task is assigned to a work team.

Table 3.8. Multiple Comparison Test for the Factor Team Size.

Conjunctive Task			Disjunctive Task			Additive Task		
TS	Mean	Grouping	TS	Mean	Grouping	TS	Mean	Grouping
1	890.1	A	3	930.5	A	2	897.3	A
2	874.9	B	2	919.7	B	3	896.8	A
3	863.1	C	5	908.0	C	1	890.1	B
4	820.7	D	4	900.3	D	4	861.3	C
5	779.6	E	1	890.1	E	5	835.3	D
6	731.3	F	6	826.6	F	6	779.7	E

[Tukey method considering a confidence level of 95%; means that do not share grouping letters are significantly different.]

For the conjunctive task, single assignments showed a higher performance than the other team sizes (Figure 3.2). For disjunctive and conjunctive tasks, teams composed of two or three workers performed best (Table 3.8). A team size of 1 showed the second lowest performance when compared against the performance of other team size scenarios defined with 2, 3, 4, and 5 workers per team for disjunctive tasks (Figure 3.2). Similarly, for additive tasks, team sizes of 2 or 3 workers per team performed better than single assignments. These results indicate that for the cases of disjunctive and additive tasks, the application of a team-based work strategy can be beneficial in specific scenarios instead of assigning workers individually to perform a task, considering the effect of process loss and knowledge transfer between workers that results from the team dynamic. Specifically, for the case of disjunctive tasks, the results suggest that the application of a team-based work strategy will have a higher impact on the system performance than the application of an individual-based work strategy.

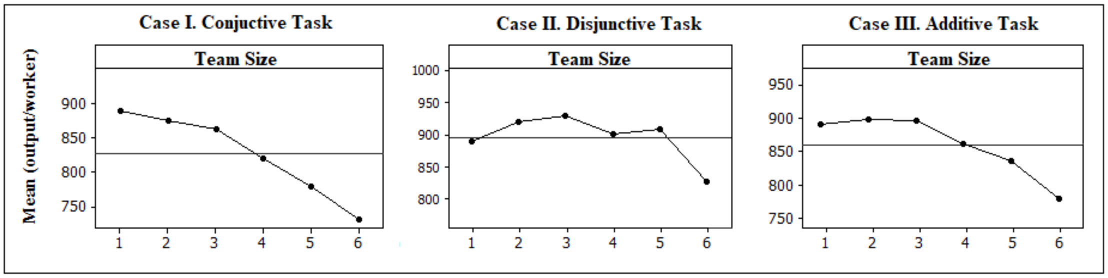

Figure 3.2. Main Effects Plot for the Factor Team Size.

The results regarding Team Size are consistent with previous literature, wherein a significant relationship has been highlighted between team size and team performance (Thomas & Fink 1963, Tohidi & Tarokh 2006, Steiner 1972, Mueller 2012, Glock & Jaber 2014, Pieltokorpi & Niemi 2018). Research has established that as team size increases, the availability of human capital to perform a specific task also increases, which can be used for workers in the team to hasten their individual learning process for a task (Nembhard & Bentefouet 2015, Mao et al. 2016, Jin et al. 2018). In particular, individuals in teams can learn from others by observing and interacting with their teammates (Destré et al. 2008, Nembhard & Bentefouet 2015, Mao et al. 2016, Jin et al. 2018). Conversely, several studies have suggested a negative correlation between team size and individual productivity in teamwork-based settings, attributing this relationship to productivity loss (Steiner 1972, Tohidi & Tarokh 2006, Mueller 2012, Pieltokorpi & Niemi 2018). Most of these studies argue that as team size increases, more coordination and effort are required of team members in order to construct relational links with colleagues in the team. Similarly, some studies argue that as team size increases, the individuals in the team experience lower levels of motivation as a result of the decrease in perception of support availability from their colleagues (Mueller 2012), as well as the decrease in individual perception of recognition (DeMatteo et al. 1998). This means that as team size increases, team members experience higher levels of productivity loss as result of coordination, relational and motivation challenges, widening the gap between the team actual performance and the team potential performance.

The proposed model in this study accounts for these two properties simultaneously. The results of the simulated experiment considering the proposed model suggest that in some scenarios of additive and disjunctive tasks, the benefits obtained by the increase of human knowledge as a result of adding an additional worker to the team exceeds the productivity loss faced as a consequence of individual motivational loss and the increase in required coordination (Figure 3.2). Thus, the selection of team size should not be considered as a straightforward decision within organizations, in order to maximize the benefits obtained through the implementation of a team-based work setting. Frank and Anderson (1971) explore the effect of group size on team performance for disjunctive and conjunctive tasks. Their findings showed that larger teams performed better for a disjunctive task. In contrast, for a conjunctive task, smaller teams showed a better team performance. These results are consistent with those found in the current study, in which larger teams showed a higher performance in disjunctive tasks, whereas for conjunctive tasks, smaller teams performed better (Figure 3.2).

Workforce Heterogeneity:

For Workforce Heterogeneity, the ANOVA showed a significant difference in system performance when considering a production system defined by a single conjunctive, disjunctive, or additive task (Table 3.5, Table 3.6, Table 3.7). To compare how different are the levels investigated as part of the factor Workforce Heterogeneity with respect to the system performance, a multiple comparison test was performed for each case using the Tukey method with a statistical confidence level of 95% (Table 3.9).

Table 3.9. Multiple Comparison Test for Workforce Heterogeneity

Conjunctive Task			Disjunctive Task			Additive Task		
WH	Mean	Grouping	WH	Mean	Grouping	WH	Mean	Grouping
50	834.4	A	150	904.6	A	150	863.1	A
100	823.1	B	100	892.9	B	50	860.4	B
150	822.4	B	50	890.1	C	100	856.7	C

[Tukey method considering a confidence level of 95%; means that do not share grouping letters are significantly different.]

For conjunctive tasks, the multiple comparison test revealed that only two of the levels investigated as part of the factor of Workforce Heterogeneity resulted in a significant difference in system performance (Table 3.9). In a conjunctive task, the level of workforce heterogeneity with respect to the learning skills will significantly impact the system performance. Specifically, in this case, higher levels of variance in the workforce with respect to the learning parameters will negatively impact system performance (Figure 3.3). For conjunctive tasks, team performance depends on the least competent member. The results for workforce heterogeneity in conjunctive tasks may be explained by the fact that higher levels of variability in the workforce increase the likelihood of having less competent workers in the team. As a consequence, higher levels of workforce heterogeneity will result in lower team performance.

These results are consistent with the discussion about heterogeneity for conjunctive tasks presented in Steiner (1972) arguing that in conjunctive tasks, having more homogeneous workers in the team results in a higher team productivity than a team composed of more heterogeneous workers. Hamilton et al. (2003) examined the effect of workforce heterogeneity on team performance in a module production setting defined by a U structure, finding in contrast that for the investigated module production setting, more heterogeneous teams resulted in a higher team productivity. The authors suggested that a possible explanation of these findings could be the effect of mutual learning between workers within teams (Hamilton et al. 2003). A possible explanation for the difference between the workforce heterogeneity findings of the present study and the results discussed in Hamilton et al. (2003) could be that the production setting analyzed in Hamilton et al. (2003) allows workers to shift and share tasks within teams. As a result, workers can help each other, thereby decreasing the effect of the slower workers in the production system. In contrast, our study considered specialized workers within teams, for whom such task-shifting may not be possible.

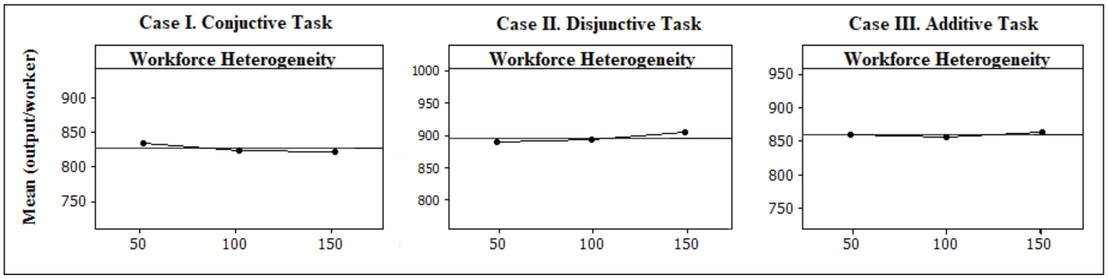

Figure 3.3. Main Effects Plot for the Factor Workforce Heterogeneity.

For disjunctive tasks, the results revealed that the three levels investigated for Workforce Heterogeneity caused a significant difference in team performance (Table 3.9). Specifically, lower levels of workforce heterogeneity showed a negative impact on the team performance. For disjunctive tasks, the team performance is defined by the most competent team member. Similar to the case of conjunctive tasks, an explanation for these results may be that as workforce heterogeneity increases, the likelihood of obtaining a more skilled worker in the team increases as well, resulting in a higher team performance. These results are consistent with the discussion of team heterogeneity for disjunctive tasks presented in Steiner (1972), which argues that for this type of task, when the performance of the team is measured on a continuous scale, having more heterogeneous workers in the team results in a higher team potential productivity. Similarly, in this case, our results showed that changing from intermediate to higher levels of workforce heterogeneity have a lesser impact on team performance than from intermediate to smaller levels of workforce heterogeneity (Table 3.9). These results suggest that as the workforce heterogeneity increases, the difference in team performance becomes less significant.

Lastly, for additive tasks, the analysis showed that all three levels investigated as part of the factor of Workforce Heterogeneity resulted in a significant difference in team performance (Table 3.9). For this case, the results showed that scenarios characterized by higher levels of heterogeneity were associated with higher team performance. However, the resulting differences in team performance between the levels of Workforce Heterogeneity explored in this study was relatively small. For additive tasks, team performance is defined by the sum of the individual team members' contributions. In this case, the average output per worker was used as the performance measure in order to correct for the scaling of larger teams for the data analysis. The current results are consistent with the results found in Shafer et al. (2001) & Steiner (1972). However, neither of these studies considered the effect of knowledge transfer within teams in addition to workforce heterogeneity and the effect of process loss. Shafer et al. (2001) investigated the impact of workforce heterogeneity on system throughput, considering the individual worker performance as a function of experience and individual ability to learn by doing. They found that higher levels of workforce heterogeneity in a system defined with independent tasks resulted in a higher system productivity than systems defined with lower levels of workforce heterogeneity. Shafer et al. (2001) suggest that this is because for heterogeneous workers, the faster workers make up for deficits from the slower workers. However, in Shafer et al. (2001), the effect of knowledge transfer and process loss which result as a consequence of the team-based work dynamic were not considered as part of the study. Steiner (1972) discussed the implications of workforce heterogeneity in team performance, suggesting that in the case of additive tasks, workforce heterogeneity will not significantly impact the potential productivity of the team. However, from a motivational perspective, workforce heterogeneity can impact the actual productivity of the team, given the individual perception of performance and workload distribution versus rewards.

The results of the current study extend the exploration of the effect of workforce heterogeneity on system performance to the context of team-based organizational settings, considering the interactions between process loss and knowledge transfer on team performance as a consequence of team size.

Knowledge Transfer:

For Knowledge Transfer, the ANOVA showed a significant difference in system performance for all three cases of production systems—conjunctive, disjunctive, or additive tasks—investigated as part of this work (Table 3.5, Table 3.6, Table 3.7). To compare the levels investigated as part of the factor of Knowledge Transfer with respect to system performance, a multiple comparison test was performed for each case using the Tukey method with a statistical confidence level of 95% (Table 3.10).

For conjunctive, disjunctive, and additive single tasks, with full knowledge transfer (KT=1), team performance is maximized (Figure 3.4). A significant difference in system performance is obtained when workers within teams take full advantage of the complete knowledge of other colleagues in the team. This ideal condition is unlikely in practice but provides a bound on what is achievable. Similarly, the results showed that the larger impact for this factor resulted from the case of non-consideration of knowledge transfer (KT =0) versus cases which did consider it (KT $\geq$ 0.25). As the amount of knowledge transfer increases, the marginal benefit in system performance from one level of KT to another decrease.

Table 3.10. Multiple Comparison Test for the Factor Knowledge Transfer.

Conjunctive Task			Disjunctive Task			Additive Task		
KT	Mean	Grouping	KT	Mean	Grouping	KT	Mean	Grouping
1.00	867.6	A	1.00	925.0	A	1.00	894.4	A
0.75	858.2	B	0.75	917.1	B	0.75	885.4	B
0.50	843.6	C	0.50	906.4	C	0.50	872.3	C
0.25	817.5	D	0.25	890.1	D	0.25	850.9	D
0.00	746.1	E	0.00	840.7	E	0.00	797.4	E

[Tukey method considering a confidence level of 95%; Means that do not share a grouping letter are significantly different.]

The results for this factor align with previous literature suggesting that individuals have the ability to use knowledge from within a team to improve their individual performance, and that the consideration of this effect is statistically significant for the task or system performance (Reagans et al. 2005; Destré et al. 2008; Nembhard & Bentefouet 2015).

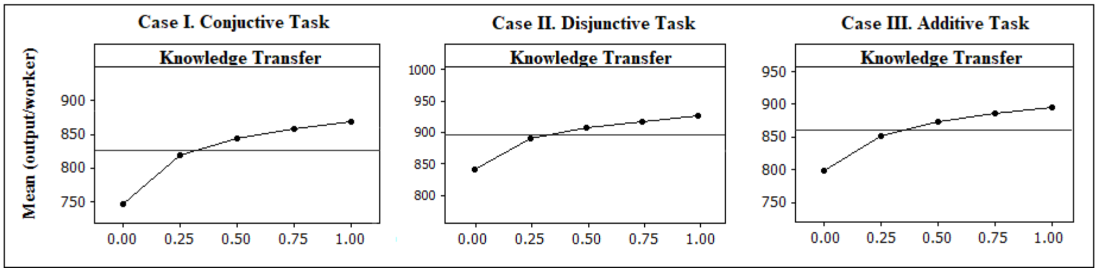

Figure 3.4. Main Effects Plot for the Factor Knowledge Transfer.

The current results extend the exploration of the effect of Knowledge Transfer on system performance to systems composed of different task types—conjunctive, disjunctive and additive tasks—considering the context of a team-based organizational setting. The current study considers the impact of the knowledge transfer between workers on individual worker performance as a function of the group size, in addition to the process loss resulting from team dynamics such as coordination, relational, and motivational processes.

Process Loss:

For Process Loss, the ANOVA showed a significant difference in system performance for all of production systems examined (Table 3.5, Table 3.6, Table 3.7). A multiple comparison test was performed for each case to compare the difference between the levels investigated as part of the factor Process Loss with respect to system performance. A Tukey method was used for this end, considering a statistical confidence level of 95% (Table 3.11).

For all three cases, the results showed that scenarios with no process loss are associated with higher team performance (Figure 3.5, Table 3.11). For all the examined cases, Process Loss had the largest impact on the team performance (Table 3.5, Table 3.6, Table 3.7). These results suggest the importance of the implementation of strategies to help reduce the effects of process loss in a team-based work environment.

Table 3.11. Multiple Comparison Test for the Factor Process Loss.

Conjunctive Task			Disjunctive Task			Additive Task		
PL	Mean	Grouping	PL	Mean	Grouping	PL	Mean	Grouping
0.00	914.7	A	0.00	986.0	A	0.00	946.6	A
0.25	880.4	B	0.25	938.9	B	0.25	911.2	B
0.50	828.5	C	0.50	903.3	C	0.50	865.0	C
0.75	779.7	D	0.75	851.1	D	0.75	814.8	D
1.00	729.7	E	1.00	800.0	E	1.00	762.8	E

[Tukey method considering a confidence level of 95%; Means that do not share grouping letters are significantly different.]

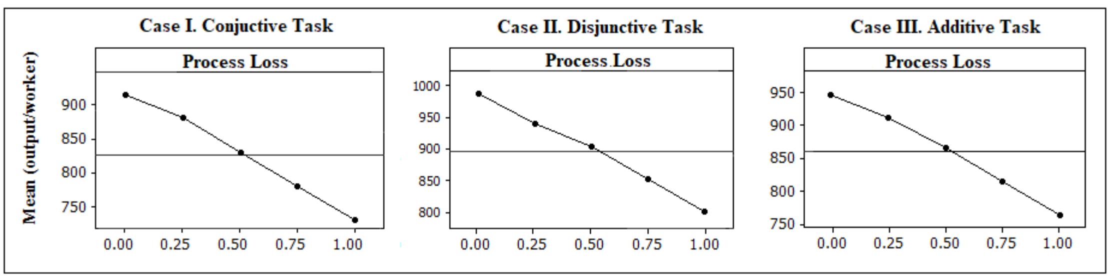

Figure 3.5. Main Effects Plot for the Factor Process Loss.

Several studies have discussed the causes and effects of process loss. Erez (1996) examined different causes of process loss, specifically social loafing, concluding that familiarity, clear goal definition, communication, and rewards have an impact on individual performance when working on team-based tasks, and consequently on team performance. Other studies of process loss have mostly focused on the effect of group size on process loss and consequently on team performance (Frank & Anderson 1971; Steiner 1972; Kameda et al. 1992; Mueller 2012; Mao et al. 2016; Peltokorpi & Niemi 2018). Mueller (2012) argues that the process loss in teams is not only a function of motivational and coordination losses, as previously explained by Stenier (1972), but also a function of relational losses. The study argued that these three components—motivational, coordination, and relational losses—are also affected by team size. Peltokorpi & Niemi (2018) studied the effect of process loss on team performance as a function of task repetition and group size considering a disjunctive task, concluding that as the team size increases, the team process loss also increases.

Other studies have investigated the effect of process loss as a consequence of individual biases and personalities (Charbonnier et al. 1998; Ogot & Okudan 2006; Hoon Tan & Li Tan 2008), arguing that cognitive biases and personality traits of team members are related to process loss and team performance. None of these studies, however, extend their analysis to explore the impact of process loss on team performance. Moreover, none of these studies extend their exploration to the effect of process loss and knowledge transfer simultaneously, as functions of team size, on team performance. The present study addresses this gap, extending the analysis of team performance to include investigation of the interactions between process loss and knowledge transfer in an operational research context.

The above results are consistent with previous findings in literature related to team dynamics, supporting the credibility of the mathematical expression presented in equation (3.2) to model workers productivity in a team context. An experimental validation of the model would be valuable as future work. However, this study will serve as a basis for further study of team dynamics from the perspective of team size, knowledge transfer, and process loss, their effects on system performance, and their application to operational research problems. Similarly, this study highlights the need for the exploration and development of mathematical models that can account for benefits and drawbacks of teamwork implementation for individual performance.

Interaction Effects:

For second order interactions for all cases, all factor interactions were significant (Table 3.5, Table 3.6, Table 3.7). This work specifically examines the interaction of Knowledge Transfer – Process Loss, Knowledge Transfer – Team Size, Process Loss – Team Size, and Workforce Heterogeneity – Team Size. In order to investigate the differences between levels of interactions, a multiple comparison test was performed, specifically using the Tukey method, considering a statistical confidence level of 95%.

For the interaction Knowledge Transfer – Process Loss (KT*PL), the results showed that for the three task types, for all levels of Process Loss, the team performance in cases that considered knowledge transfer was significantly different from cases that did not consider it (Figure 3.6). These results suggest that the consideration of knowledge transfer can make a significant difference in the team performance even in cases where there is no process loss. In addition, for all three cases, as the degree of Knowledge Transfer increases through the different levels of process loss, the increases in team performance consistently showed a diminishing marginal productivity. That means that as Knowledge Transfer increases, the benefit that team members obtain from the effect of Knowledge Transfer decreases.

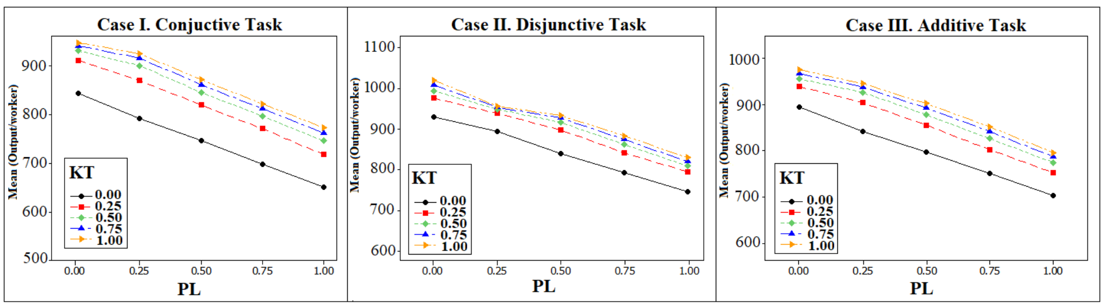

Figure 3.6. Knowledge Transfer-Process Loss Interaction Plot.

Regarding the impact of the joint effect of knowledge transfer and process loss in team performance and optimal team size, specifically for the conjunctive task case, in scenarios with no knowledge transfer (KT = 0), the best system performance was obtained in systems with team sizes of 1 worker per team (Figure 3.7). For this scenario the multiple comparison test revealed the performance associated with TS=1, was significantly higher than for larger teams. For scenarios defined by some degree of Knowledge Transfer (KT > 0), the results showed that larger team sizes (TS ≥ 3) had a significant higher performance than smaller teams. However, teams with more than two workers (TS ≥ 3) did not differ in their performance. As the degree of Knowledge Transfer and Process Loss increases, the difference between the performance of all the evaluated team sizes becomes significant, where for KT ≥ 0.25 and PL ≥ 0.75 teams composed of three workers in average performed significantly better that all other team sizes.

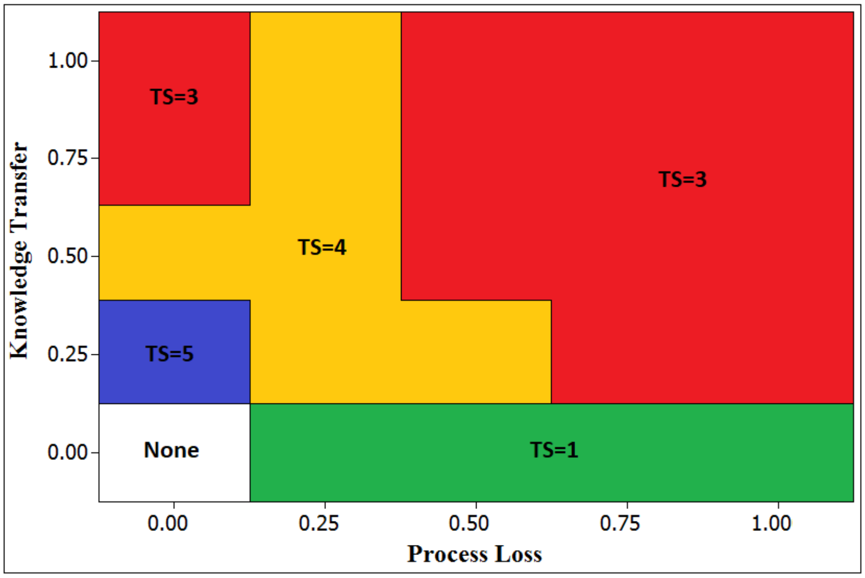

Figure 3.7. Optimal Team Size by Levels of Knowledge Transfer and Process Loss: Conjunctive Task Case

For the case defined by a disjunctive task, and no process loss, the larger teams (TS > 4) performed significantly better than smaller teams (Figure 3.8). For non-knowledge transfer scenarios (KT = 0) smaller teams are preferred as the degree of process loss increases. Specifically, for scenarios with greater process loss (i.e., $PL \geq 0.5$), the different team sizes did not perform significantly differently ($TS \geq 2$). In the case of a system defined by a single disjunctive task, as the degree of Knowledge Transfer and Process Loss increases (PL & $KT \geq 0.25$), teams composed of 3 workers in average performed equally or better than the other team sizes.

Lastly, for a single additive task, with no process loss, larger teams (TS ≥ 4) are associated with a significant higher performance than smaller teams (Figure 3.9). With no knowledge transfer (KT = 0) single-based task assignment (TS=1) is better than larger teams (TS ≥ 2) across levels of process loss other than zero (PL>0). The additive case is similar to the disjunctive case, where as the degree of Knowledge Transfer and Process Loss increases (PL & KT ≥ 0.25), teams composed of 3 workers performed equally or significantly better. Then for these scenarios, teams composed of three workers are preferred.

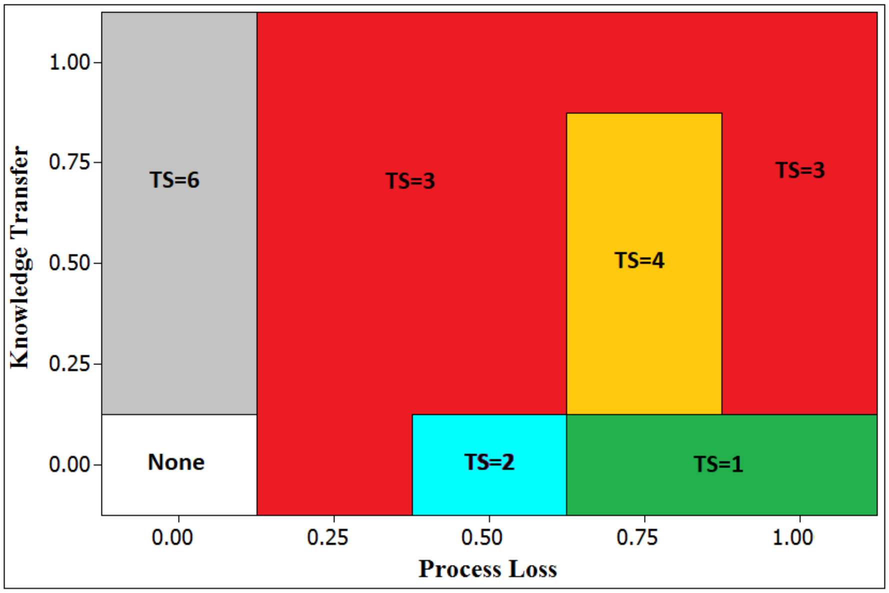

Figure 3.8. Optimal Team Size by Levels of Knowledge Transfer and Process Loss: Disjunctive Task Case.

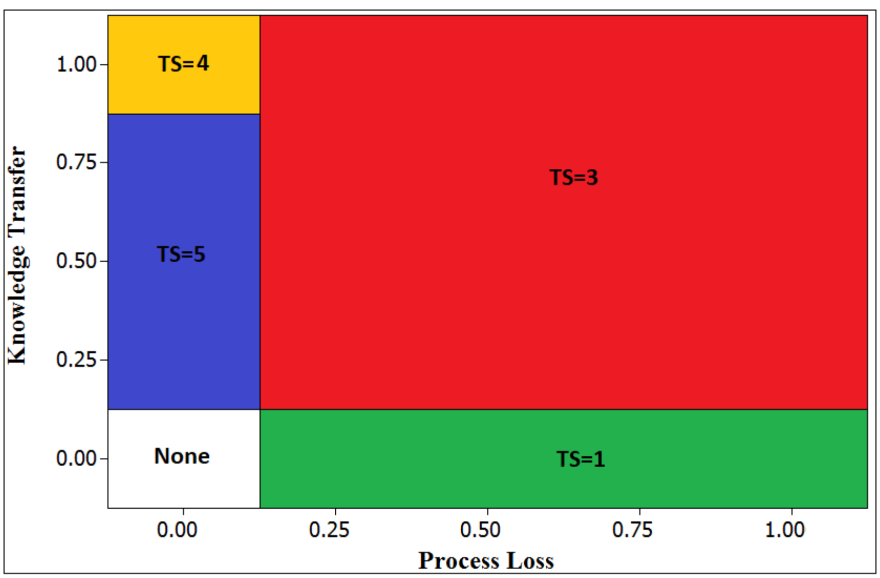

Figure 3.9 Optimal Team Size by Levels of Knowledge Transfer and Process Loss: Additive Task Case.

For the interaction Knowledge Transfer – Team Size (KT*TS), the results revealed that for scenarios where no knowledge transfer was considered (*KT* = 0), as team size increased, the system performance decreased systematically without exception for all three task types. However, for scenarios where knowledge transfer was considered ($KT \geq 0.25$), larger team sizes in some cases resulted in a higher system performance than smaller team sizes (Figure 3.10). These results suggest that the effect of knowledge transfer can significantly benefit team performance. In general, for most levels of Team Size, performance significantly differed among scenarios of knowledge transfer. Specifically, for disjunctive and additive tasks, as team size increases the difference in team performance between the knowledge transfer levels, becomes wider until TS=5 and, and then narrows for TS=6. These results suggest that in team-based work settings, the impact of knowledge transfer between workers would benefit team performance, surpassing the impact of team process loss until a maximum team performance P^* is reached for a specific team size TS^*. However, as team size increases beyond TS^*, the impact of process loss surpasses the benefits obtained from knowledge transfer between workers, resulting in the decrease of team performance under P^*. These results are consistent with the findings of previous work which highlighted the benefits of a teamwork strategy for system performance, and which found that optimal team size varies depending on the task type and the context in which the teamwork strategy is implemented (Manners 1975; Kameda et al. 1992; Tohidi & Tarokh 2006; Akinola & Ayinla 2014).

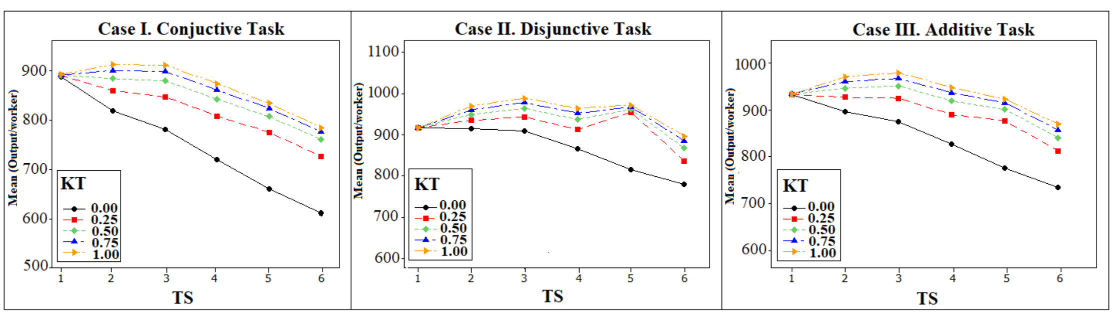

Figure 3.10. Knowledge Transfer-Team Size Interaction Plot.

For the interaction Process Loss - Team Size (PL*TS), the results from the multiple comparison revealed that for the three investigated task types and for almost all levels of Process Loss, team performance is significantly different for teams of different sizes (Figure 3.11). Specifically, the results showed that as Team Size increases, the impact of the degree of process loss becomes greater. These results extend related concepts in previous literature, in which a positive relationship between process loss and team size has been suggested (Steiner 1972; Kameda et al. 1992; Mueller 2012; Peltokorpi & Niemi 2018). Studies have attributed this relationship between process loss and team size to issues of coordination, communication, and motivation that arise as more members are added to a team to conduct a specific task (Steiner 1972; Mueller 2012).

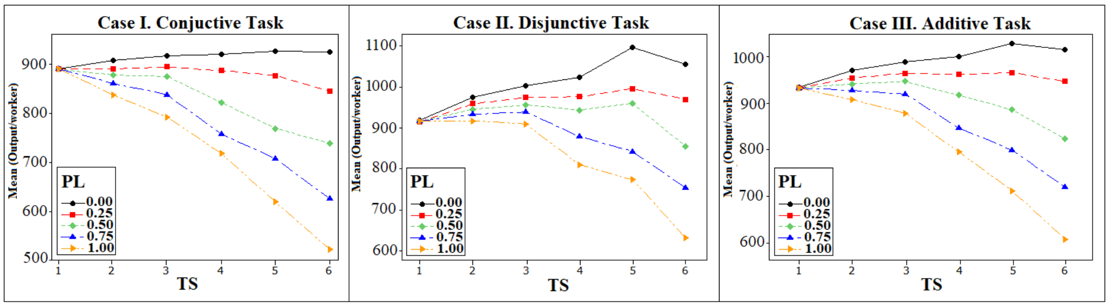

Figure 3.11. Process Loss -Team Size Interaction Plot.

For the Workforce Heterogeneity – Team Size interaction (WH*TS), the results from the multiple comparison revealed that for team sizes greater than one, scenarios with lower levels of workforce heterogeneity consistently resulted in a significantly higher team performance than scenarios with higher levels of heterogeneity in the case of a system composed of a single conjunctive task (Figure 3.12). Similarly, the results showed for this case that as team size increases the difference in performance among levels of heterogeneity increases. In the case of a production system composed of a single disjunctive task, the results showed that in all cases of team size, scenarios with higher levels of workforce heterogeneity consistently resulted in a significantly higher team performance than scenarios with lower levels of heterogeneity (Figure 3.12). Finally, for the case of a production system composed of a single additive task, the results showed that for almost all explored levels of the factor Team Size, $TS \geq 2$, team performance in scenarios with lower levels of workforce heterogeneity was not significantly different from team performance in scenarios with higher levels of workforce heterogeneity (Figure 3.12). Specifically, higher levels of Heterogeneity were associated with higher team performance, and as Team Size increases, the impact of the degree of workforce heterogeneity decreases.

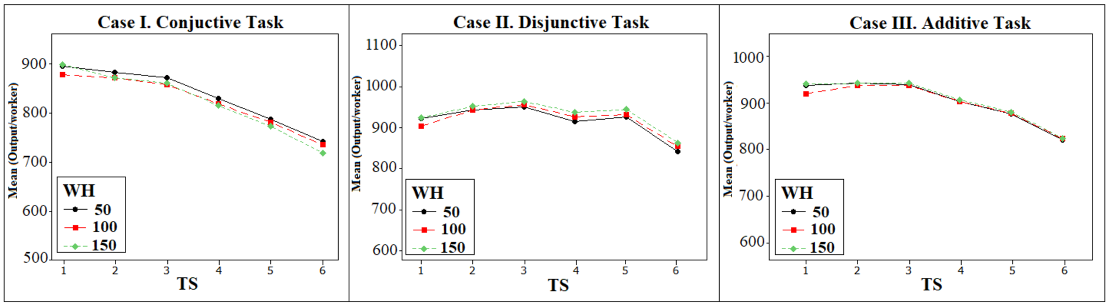

Figure 3.12. Process Loss -Team Size Interaction Plot.

3.5 Conclusions and Managerial Implications

The purpose of this paper was to explore the effect of team size on team performance, considering the effect of knowledge transfer between workers and process loss. Previous research has studied the relation between team size and knowledge transfer, arguing that as more workers are added to the team, the available resources the team has to complete the task increases as well. Similarly, previous research has also found a relationship between process loss and team size. Specifically, studies have demonstrated that as team size increases, the gap between the potential productivity and the actual productivity of a team also increases as a result of motivational, relational, and coordination issues that arise within teams. We evaluated the joint effects of knowledge transfer and process loss on team performance, and how decisions related to team size are impacted in conjunctive, disjunctive, and additive tasks. Studies exploring team formation and as well models to estimate individual performance considering the joint effect of knowledge transfer and process losses are notably absent in the literature.

The study was performed though the simulation of three types of production systems, represented by a single conjunctive, disjunctive, and additive task, respectively. The study examined different experimental factors such as degree of process loss, degree of knowledge transfer, team size, and workforce heterogeneity. Workforce heterogeneity was considered through the estimation of individual worker productivity as a function of the cumulative experience on the task, the effect of process loss as a function of team size, and the individual capacity for learning by doing and by knowledge transfer. The research questions investigated were: (1) How does optimal team size change for different levels of a) workforce heterogeneity, b) process loss, and

c) knowledge transfer in conjunctive, disjunctive and additive tasks? and (2) What team sizes are best across different levels of Knowledge Transfer and Process Loss? Similarities and contrasting results were found between the three explored cases of systems. We organize these broad findings into four areas below:

1. In all three examined task types—conjunctive, disjunctive and additive tasks—Team Size (TS) had a significant effect on team performance, highlighting the importance of its consideration as part of a teamwork strategy implementation in production systems. The application of a teamwork strategy was shown to be beneficial for team performance in some task scenarios, instead of assigning workers individually to perform tasks, when considering the effect of process loss and knowledge transfer between workers. Nonetheless, the selection of the implementation of a teamwork strategy—more specifically the tuning of factors, such as team size selection, that helps to maximize the benefit of this strategy—is not a straightforward decision process. Frank and Anderson (1971) explored the effect of group size on team performance for disjunctive and conjunctive tasks. Their findings showed that larger teams performed better for a disjunctive task. In contrast, for a conjunctive task, smaller teams exhibited better team performance. The results were consistent with these findings.

   The managerial implications of these findings suggest that for disjunctive, conjunctive and additive tasks managers should consider the application of a team-based work strategy over a single-assignation strategy. Specifically, as a rule of thumb, for conjunctive and additive tasks, the assignation of workers into smaller teams would benefit team performance. However, for disjunctive tasks, managers might consider somewhat larger teams, generally.

2. Workforce Heterogeneity (WH) had a significant effect on team performance for each task type—conjunctive, disjunctive and additive. Current findings suggest the importance of workforce heterogeneity as part of implementing a teamwork strategy. The degree to which team performance is affected by workforce heterogeneity will depend on the task type, team size, degree of knowledge transfer,

and degree of process loss for conjunctive, disjunctive, and additive tasks. Although workforce heterogeneity had a significant impact on team performance, for all three task types, this factor showed a lower impact on team performance when is compared to team size, process loss and knowledge transfer. These results highlight that managers should prioritize the modeling and consideration of others factors such as team size, knowledge transfer and process loss over workforce heterogeneity.

Specifically, for conjunctive tasks, higher levels of workforce heterogeneity with respect to the learning parameters are associated with lower levels of system performance. In contrast, for disjunctive and additive tasks, the results suggested that higher levels of workforce heterogeneity are associated with higher levels of team performance. Although the effect of workforce heterogeneity has been examined in previous works, this factor has been investigated in isolation from the simultaneous effect of knowledge transfer and process loss (Steiner 1972, Shafer et al. 2001; Hamilton et al. 2003). The current study intends to fill this gap in literature.

3. Knowledge Transfer (KT) had a significant positive effect on team performance in the three investigated task types. Previous studies demonstrated the individual capacity to use knowledge from within a team to improve individual performance (Hendricks 1996; Reagans et al. 2005; Knockaert et al. 2011; Baeten & Simons 2014; Glock & Jaber 2014; Nembhard and Bentefouet 2015, Jin et al. 2018). The results of the current study revealed that the larger difference in team performance related to the factor Knowledge Transfer resulted from work scenarios where no knowledge transfer (KT=0) takes place, which represents the case in which no individual benefit is obtained from the knowledge of other colleagues within the team, versus cases where some degree of knowledge transfer between team members occurs (KT≥0.25). As the amount of knowledge transfer increases, the marginal benefit in system performance from one level of KT to another decrease. Similarly, for scenarios where no knowledge transfer was considered (KT=0), as team size increased, the system performance decreased systematically without

exception for all three investigated task types. However, for scenarios where knowledge transfer was considered (KT≥0.25), larger team sizes in some cases resulted in a higher system performance than smaller team sizes. From a managerial perspective the results of the current study related to the factor Knowledge Transfer suggest the consideration of implementing a team-based work strategy in order to benefit from the effect of knowledge transfer between workers and hasten the learning process of workers within the team. In some work conditions, considering production systems composed of conjunctive, disjunctive, or additive tasks, the effect of knowledge transfer can significantly benefit team performance, surpassing the effect of process loss incurred within a team and making larger instances of team size profitable. Similarly, managers might consider the development of strategies that facilitates communication and interaction between workers within teams in order to ensure that knowledge transfer occurs in work teams.

4. Scenarios where no process loss is faced were associated with higher levels of team performance. Previous studies have demonstrated that as team size increases, the team dynamic related to coordination and establishing relational and communication links between members within the team becomes more complex. Similarly, the motivation of individuals within teams decreases as team size increases, making workers perform under their individual potential productivity. As a consequence, the gap between team potential productivity and team actual productivity widens as team size increases (Steiner 1972; Mueller 2012). The results of the current study are consistent with previous findings showing that as team size increases, the negative impact of process loss on team performance becomes stronger. One contribution of the current study is to extend the analysis of team performance given the trade-off between process loss and knowledge transfer in an operation research context. This study explores the impact of different levels of process loss and knowledge transfer on team performance, considering the interaction between both factors as part of the analysis. Previous studies did not consider the interaction between these two factors as part of the team formation problem. The current study will serve as a base for exploring team dynamics from the perspective of team size, knowledge transfer, and process loss, on system

performance and the application of this knowledge to address operation research problems. Similarly, this study highlights the need to explore and develop mathematical models that account for the benefits and drawbacks of teamwork implementation for individual performance.

The current work is based on a broad range of individual behaviors, where in future work, this may be based on empirical distributions of these behaviors. The proposed model represents a hypothetical case of team context, assuming that in these scenarios, individual worker performance is directly proportional to the effect of process loss. The development of mathematical models, derived from experimental data, that relate the effect of knowledge transfer and process loss to individual worker performance in teamwork contexts remains a gap in the teamwork literature and will be an area of interest for future research.

Prior literature states that process loss decreases through the experience of becoming familiar with the process, members, and responsibilities within the team (Steiner 1972; Reagans et al. 2005; Huckman et al. 2009; Peltokorpi & Niemi 2018). The proposed model represents a hypothetical case of team context, assuming that in these scenarios the individual worker performance is directly proportional to the effect of process loss. The development of mathematical models derived from experimental data that relate the effect of knowledge transfer and process loss with the individual performance in teamwork contexts remains a gap in the literature on teamwork.

Future research may include the development of methods to address team formation as part of the worker-assignment problem, considering both process loss and knowledge transfer as results of team dynamics. Similarly, a future study will consider the extension of the team formation problem, considering the joint effect of knowledge transfer and process loss on team performance, to a larger instance representing a broader organizational context. Also, the exploration of additional factors such as production system structures considering different types of tasks as well as different scenarios of workforce availability for the team formation problem, considering both process loss and knowledge transfer, will be an area of interest for future studies.

CHAPTER 4

Multiple-Team Formation Considering Knowledge Transfer and Process Loss.

Abstract

This study investigates the team formation problem in an organizational context, considering the effect of knowledge transfer and process loss on system performance. The performance of teams has been related to individual worker advantages from knowledge transfer within a team, as well as disadvantages from the effects of losses due to the communication overhead among team members. Larger teams provide access to greater resources with respect to assistance, knowledge sharing, and accumulated experience within a team. However, larger teams also face challenges in coordinating tasks between members, establishing relations within the team, and maintaining the motivation of individual team members. Thus, the informed selection of team size is necessary in order to obtain the maximum benefit of a teamwork strategy implementation. This problem may be formulated as a Mixed Integer Nonlinear Program (MINLP). However, the traditional method for addressing this type of problem often only yields results for very small problem instances. The development of a closed mathematical expression to determine the optimal team size without solving the MINLP for the specific problem will mitigate some of the computational complexity associated with the problem and will also help to increase the maximum size problem instance that can be solved by exact optimization methods. In this work, the team formation problem is examined with the aim of developing a mathematical expression to determine the optimal team size in a multiple work-team setting, considering homogeneous tasks and a heterogeneous workforce within solving an MINLP. The effect of knowledge transfer and process loss on individual performance will be considered as part of the study to represent the effect of workers' interaction within a team on the individual worker's productivity.

4.1 Introduction

Teamwork has been extensively used by organizations to increase production capacity, improve process efficiency, boost the learning process of novice workers, or just out of a need to perform specific operations that cannot be carried out in a single work setting. In general, teams have been defined as a group of agents working together to accomplish a specific goal (Bursic 1992; Cohen & Levesque 1991), where the performance of the team not only corresponds to the addition of the potential performance of individual team members but also depends on many factors such as members' interaction within the team, organization factors, task type, and team design factors (Steiner 1972; Doolen et al. 2003).

Extensive literature has been dedicated to exploring the different factors that affect team performance in organizations as well as the search for strategies to maximize the benefits obtained from the implementation of this strategy. One factor that has been extensively studied and discussed in the literature of teamwork is the team size, specifically the question of how to select the optimal team size in order to maximize team performance. The number of individuals assigned in teams has been associated with the amount of resources, skills, and knowledge that teams have to complete a specific task, but also with the level of required coordination and relational links that members within teams should have in order to perform efficiently as a team (Steiner 1972; Peltokorpi & Niemi 2018). Similarly, previous studies have argued that the number of individuals in teams can affect the individual motivation of team members, in some instances causing members to perform below their individual potential capacity, given lack of motivation (Kameda et al. 1992; Steiner 1972; Mueller 2012). Therefore, the selection of the appropriate team size is not a straightforward decision for managers when the implementation of a teamwork strategy is considered for an organization.

Several studies have investigated the effect of team size on team performance, most of them through the use of observational field approaches (Tomad 1963; Frank & Anderson 1971; Manners 1975; Kameda et al. 1992; Esteban & Ray 2001; Nosenzo et al. 2005; Barcelo & Capraro 2015; Mao et al. 2016; Tohidi & Tarokh 2006; Ogungbamila et al. 2010; Mueller 2012; Akinola & Ayinla 2014; Peltokorpi & Niemi

2018). These studies have concentrated on exploring the correlation between team size and team performance for different kind of settings and tasks.

However, few studies have focused on the development of strategies to address team formation, or more specifically to determine the optimal team size in an organizational context when considering gaining and losses of a teamwork policy. Production floors and organizations in general are often composed of multiple tasks or projects that need to be realized simultaneously. Thus, considering an organizational context defined by a multiple-team setting, as well as the effect of process loss and knowledge transfer on the individual productivity, will provide a more realistic and complete view of the system performance when evaluating the implementation of teamwork policies. Addressing this gap can benefit organizations by providing a more realistic estimation of the system performance when evaluating the implementation of teamwork policies in the organization, consequently helping managers make more accurate decisions with respect to workforce management plans.

This work aims to explore the team formation problem in an organizational context, considering the joint effect of knowledge transfer and process loss on individual performance, wherein individual performance has been defined as worker's productivity. Specifically, the problem involves the determination of the optimal team size when considering an organization composed of multiple teams, wherein the productivity of the workers who compose the workforce is defined by their individual learning characteristics and the effect of team dynamic. The effect of team dynamic on individual productivity is modeled as a function of knowledge transfer and process loss. A closed mathematical expression is presented toward this end, focused on determining the optimal team size when considering a multiple-team environment and the effect of experiential learning, knowledge transfer, and process loss on the individual workers' productivity. The main contribution of this work is the development of a mathematical expression which will allow managers to determine the optimal team size for a multiple-team environment without the need to solve the MINLP when considering the learning effect on worker productivity. Therefore, this study will facilitate managerial-level decisions on team formation at the enterprise scale, where balancing team workloads and inter-team movements poses additional decision-making challenges.

The multiple-team formation problem has not been previously studied considering the effect of process loss and knowledge transfer simultaneously on system performance. Therefore, the current study will contribute to this gap on literature. The remainder of the manuscript is organized as follows: Section 4.2 presents a review of the literature related to existing methods to address the multiple-team formation problem and their advantages and limitations. Section 4.3 describes the proposed method to address the team sizing problem. Section 4.4 presents the conclusions and final remarks of the study.

4.2 Literature Review

The team formation problem has been barely addressed in literature, although the common practice of the implementation of teamwork in organizations. Teamwork literature mainly focuses on the exploration and understanding of factors that affect team performance (Alavi 1994; Doolen et al. 2003; Knozlowski & Ilgen 2006; Choi 2008; Piña et al. 2008; Jaca et al. 2013), where some of the factors that have been identified as significant predictors of team performance are team composition (Webb 1995; Drach-Zahavy & Somech 2001; Hamilton et al. 2003; Ogot & Okudan 2006; Peeters et al. 2006; Mathieu et al. 2008; Knockaert et al. 2011; Shin et al. 2012; Rhee et al. 2013; Chen & Chang 2016), reward systems (Elliott & Meeker 1984; Deamatteo et al. 1998; Wickramasinghe & Widyaratne 2012), team size (Thomas 1963; Frank & Anderson 1971; Manners 1975; Kameda et al. 1992; Esteban & Ray 2001; Nosenzo et al. 2005; Barcelo & Capraro 2015; Mao et al. 2016; Tohidi & Tarokh 2006; Ogungbamila et al. 2010; Mueller 2012; Akinola & Ayinla 2014; Peltokorpi & Niemi 2018), communication between members (Erez & Somech 1996; Mathieu et al. 2008; Macht et al. 2014;) and members familiarity (Reagans et al. 2005; Mathieu et al. 2008; Huckman et al. 2009).

Specifically, team size has been one of the factors that has received significant attention in literature of teamwork. Team size have been recognized as a significant predictor for team performance. Team size have been highlighted in some works as advantageous for team performance, recognizing that as team size increases the potential capacity of the team to perform the task as well increases (Steiner 1972;

Mueller 2012; Peltokorpi & Niemi 2018). Teams that are composed for a large number of members have more available human capital to successfully perform the task than smaller teams. Similarly, studies have argued that larger teams not only have more available human capital to perform a task, but also have more available knowledge that can be learnt and used for individuals within the team to improve their individual performance and consequently the team performance (Glock & Jaber 2014; Nembhard & Bentefouet 2015).

However, a counterpart of team size that have been argued in literature by several studies is it relation with process loss. Although larger teams have a larger human capital to perform tasks, also larger teams need higher amount of coordination and relational links between members to successfully achieve their goals (Steiner 1972). That means, larger teams tend to spend more time trying to decide how to divide tasks and responsibilities between team members and how organizing the work in general. Also, in larger teams, individuals spend more time establishing relationships and knowing others in the team due that exists a large number of members with whom they need to interact and construct relational links (Steiner 1972). Finally, teamwork literature has been argued as well that in larger teams, individuals faced lower levels of motivation to perform at their potential capacity due the individual perception of recognition, rewards and support availability from colleagues in the team (Steiner 1972; Mueller 2012). Then, as consequence of these processes related with coordination, members relations, and member's motivation, larger teams tends to perform below their potential capacity, and this phenomenon has been recognized in the literature as process loss (Steiner 1972; Mueller 2012; Peltokorpi & Niemi 2018).

Although numerous studies have been dedicated to exploring the implementation of teamwork in organizations, specifically related to examining the effect of team size on team performance in field studies, most of them have not been extended to the application and development of team formation models.

Askin & Huang (2001) proposed a model for team formation considering team members synergy and skills coverage. The proposed formulation to address the formation of teams did not account for the quantitative impact of members' interaction within the teams on team performance and did not considers the effect of team size on team performance from the perspective of process loss or knowledge transfer between workers. In Nembhard & Bentefouet (2015) and Jin et al. (2018) is addressed the team formation problem considering the effect of knowledge transfer between workers as function of team size on system performance. Nembhard & Bentefouet (2015) proposed a set of heuristic policies to facilitate the process of team formation and worker assignment for serial and parallel manufacturing systems, while Jin et al. (2018) proposed a mathematical reformulation technique in order to solve to optimality the original MNLIP problem as a MLIP problem. Both studies considered the workforce heterogeneity and the learning process of workers. However, a limitation of both studies is that none of both considered the effect of process loss as part function of team size for the team formation process.

Walter & Zimmermann (2016) addressed the multiple team formation problem considering the minimization of team size as performance measure. The work established the decision of the selection for the performance measure based on the knowledge related to team size and process loss in teams. However, the process loss was not directly considered as part of the mathematical formulation. The method focused specifically in the formation of teams to complete projects, where skill requirement coverage is a constraint of the problem. In Farasat & Nikolaev (2016) the team formation problem has been addressed using social network analysis. The team formation problem in this work was addressed considering the maximization of average output across all teams as objective function and the effect of members interactions within teams in the teams' outputs in the form of homophily which is related with the similarity of members with respect to technical and personal attributes, transitivity which correspond to the flow of information and communication within the teams, contagion signals which represents the degree of popularity of members in the team, network evolution which is related with personal utility and happiness of team members, and structural hole which correspond to amount of information flow between members. Although the proposed method account for the effect of interaction between members from the social interaction perspective, the effect of process loss as function of team size is not considered as part of the model. Previous studies have showed the impact of process loss in team performance, which is specifically critical as team size increases. Similarly, the model considered constant production rates of workers, which assumes that the system has reached a steady state level.

The multiple team formation problem considering the simultaneous effect of process loss, knowledge transfer, and workforce heterogeneity on system performance has not been addressed before. The current study will address this gap focusing on the multiple team formation problem considering the factors previously described in order to generate a mathematical expression that facilitates the determination of the optimal team size in multiple team settings when considering team dynamics from the effect of knowledge transfer and process loss on individual productivity. The study further intends to generate knowledge to inform managerial decisions related to team formation in enterprise settings and to serve as intermediate step for further application to simplify the formulation of additional problems related to the development of workforce management plans in organizations that considers a team-based assignation rule policy.

4.3 Problem Description

The team sizing problem (TSP) pertains to determining the optimal team size when dividing a group of people into teams. This work specifically addresses the TSP for an organizational context, considering a multiple team environment, workforce heterogeneity, and different task types. Workforce heterogeneity is considered based on individual productivity, wherein the individual productivity is calculated considering learning by doing, knowledge transfer, and process loss. The effect of knowledge transfer and process loss on individual performance are functions of the team size and represent the effect of team dynamic on individual performance, which in this work has been defined as individual productivity. Learning by doing is a function of individual experience, wherein the individual experience is considered in terms of units of time that a worker has spent performing a task. In general, the individual productivity is estimated using a modification of the 3-parameter exponential learning curve (Anzanello & Fogliatto 2011), incorporating the effect of team dynamics on individual productivity through the concepts of knowledge transfer and process loss.

Three organizational task types are considered as part of the problem: additive tasks defined as Case I, conjunctive tasks defined as Case II, and disjunctive tasks defined as Case III. Each case represents a pure production system, wherein only one task type is considered. Hybrid cases of task types are not part of the scope of this work. Similarly, two specific scenarios of the problem have been addressed. The first scenario corresponds to a production system comprising a homogeneous workforce, wherein teams are constructed by assigning an equal number of workers within each team. The second scenario corresponds to a production system comprising a heterogeneous workforce, wherein teams are constructed by assigning an equal number of workers within each team. The heterogeneity of workers for the second scenario has been modeled with respect to the individual learning characteristics that are used to estimate individual productivity for each time period. The consideration of different team sizes within the production system is out of the scope of this work but remains of interest for future research. The assumptions and limitations of this work are described below.

4.3.1 Assumptions

The problem described in this work has been addressed considering the following assumptions:

- There are *n* workers available to perform the tasks.
- The examined cases consider pure production systems which for Case I examine a system composed of additive tasks, for Case II examine a system composed of conjunctive tasks, and for Case III examine a system composed of disjunctive tasks. The model does not consider hybrid scenarios of these cases.
- The production system is divisible and its process is flexible. This means that the number of tasks within the production system is determined by the number of teams created as part of the team formation process, where each task in the production system is assigned to only one team and vice versa.
- The system productivity is defined by the *sum of teams' productivity*, where the team productivity is determined by the task type of the production system. This means that the production system considered in this work assumes that tasks assigned between teams in the system are independent.

- A fixed time horizon of v = 50 time periods is considered in the model. The time horizon was selected considering a length of time sufficient to capture the learning process of workers but not so extended that the learning process effect is lost for the steady state behavior in the long run.
- The rate of learning is a function of how much time the worker has spent performing a particular task in a team with m-1 teammates and of the percentage of knowledge that can be transferred (θ) from teammates.
- The process loss is a function of the team size m and the percentage of productivity that is lost (δ) given coordination, motivational, and relational issues that workers face within the team.
- Workers are heterogeneous with respect to the worker's previous experience p, the steady state level k that will be achieved when the worker completes the learning process, and the cumulative production required to achieve a k/2 level of performance, represented by the parameter r.
- The work considers an organizational context defined as a production system composed of multiple teams, wherein each team is assigned an equal number of workers. Therefore, teams within the production systems are homogeneous with respect to team size.

4.3.2 *Mathematical Expression to Determine Optimal Team Size*

In this section, a mathematical expression is presented to determine the optimal team size when considering experiential learning, knowledge transfer, and process loss for different production systems scenarios. A modification of the 3-parameter exponential learning curve model is used (Eq. 4.1) to estimates individual worker productivity considering the effect of team dynamic on workers individual productivity, defining team dynamic in terms of knowledge transfer and process loss.

$$y_i(x,m) = k_i(1-\delta L_m)\left(1-e^{\frac{-(x+p_i+R)}{r_i}}\right) \quad \forall i \in I \tag{4.1}$$

Model 4.1 quantifies productivity, $y_i(x, m)$, of worker i, when is assigned to a team of size m, after acquiring x units of experience in time in the operation. The model considers worker's previous experience in the particular operation represented by parameter p, productivity steady state that a particular worker can achieved when the learning process in the operation is completed represented by parameter k, and the cumulative production required to achieve a $k/2$ level of performance represented by the parameter r. Parameter R represents the effect of knowledge transfer, which means the knowledge that a worker can obtain from other colleagues working together in similar tasks to improve their own performance, defining as $R = (m-1)x\theta$. Parameter m and θ are defined as the team size in terms of number of workers assigned in the particular team and the percentage of knowledge transferred from other workers performing similar tasks (Nembhard & Bentefouet 2015) respectively. Lastly, parameters L_m and δ account for the effect of process loss, representing the maximum fraction of productivity that can be lost for a specific team size and the percentage of process loss that is applied for the specific scenario respectively. In general, parameter L_m and δ quantifies the percentage of individual productivity that is lost from the need for required coordination, the need to build relationships and communication links with other individuals in a team, and the loss of motivation that results from working in a team context of a specific size. The parameter L_m has been estimated through the lineal regression function $L_m = -0.1 + 0.09m$, which was fitted with data presented in Peltokorpi and Niemi (2018). Parameters θ, and δ are bounded by 0 and 1.

The integration of this model with respect to x (Eq. 4.2), describes worker production output over the time horizon $[a,b]$ for a worker i assigned to a team of size m, and it has been defined in the formulation as $F_i(m)$ (Eq. 4.3).

$$F_i(m) = \int_a^b k_i(1-\delta L_m)\left(1 - e^{-\left(\frac{x + \theta x(m-1) + p_i}{r_i}\right)}\right)dx \qquad (4.2)$$

$$F_i(m) = k_i(1-\delta L_m)\left(\frac{r_i}{1+\theta(m-1)} e^{-\left(\frac{x + \theta x(m-1) + p_i}{r_i}\right)} + x\right)\Bigg|_a^b \quad \forall i \in I \qquad (4.3)$$

Homogeneous Team Size – Homogeneous Workforce

The scenario of homogeneous team sizes and homogeneous workforce represents the case where it is assumed that there is no difference between workers with respect to their productivity rate vs time, and wherein all workers are assigned to teams of equal size. That means that all workers produce at the same rate, and same number of workers are assigned to every team that composed the system. Therefore, when considering an homogeneous workforce the expression to calculate production output over the time horizon [*a*,*b*] for a worker *i* assigned to a team of size *m* is simplified to equation 4.4.

$$F(m) = k(1-\delta L_m)\left(\frac{r}{1+\theta(m-1)}e^{-\left(\frac{x+\theta x(m-1)+p}{r}\right)}+x\right)\Bigg|_a^b \tag{4.4}$$

A function $G(m)$ is defined in equation 4.5 in order to rewrite the expression to calculate production output previously presented in equation 4.4 for this specific scenario, wherein for simplification of the notation function *G(m)* has been referred in the following expressions through this work as G_m. This step has been applied to present the results later in this work in a more concise way. Therefore, equation 4.6 presents the expression to calculate production output over the time horizon [*a*,*b*] for a fixed set of homogeneous workers assigned teams of size *m* considering the function G_m.

$$G_m = \frac{r}{1+\theta(m-1)}e^{-\left(\frac{x+\theta x(m-1)+p}{r}\right)}+x\Bigg|_a^b \tag{4.5}$$

$$F(m) = k(1-\delta L_m)G_m|_a^b \tag{4.6}$$

Three different cases of production systems are considered in this work: Case I. additive tasks type, Case II. conjunctive task type, and Case III. disjunctive tasks type. The production systems considered in this work consists of a homogeneous structure. That means for example that for Case I the production system is composed only of multiple pure additive tasks. The scope of this work does not extend to the analysis of hybrid production systems composed of multiple task types.

Case I) Additive Task Type

The production system evaluated in this section consist of a system composed of multiple *additive* tasks. An additive task has been defined as a task where the individual contributions of the team members are combined as a single output. Then, the team performance for additive tasks is determined by the sum of the individual contributions of all team members (Steiner 1972). In this work, team performance has been defined as the team total output through a time horizon of 50-time periods. Specifically, for a system composed of additive tasks, this work defines team total output as the sum of the individual total output of the workers that composed the team for the time horizon $[a,b]$. System output is defined as the summation of teams' outputs, considering that tasks between teams are independent. The production system described in this scenario considers a fixed homogeneous workforce composed of W workers and W/m homogeneous additive tasks. Each task in the production system is assigned to one only team and vice versa.

Using the expression presented in equation 4.6, Theorem 1 developed. Theorem 1 presents an expression to determine the optimal team size for production systems composed of multiple additive tasks, when considering a homogeneous workforce and homogeneous team sizes within the system as previously described.

Theorem 1) When maximizing system productivity, with a performance model that considers the effect of experience, knowledge transfer and process loss to estimate individual workers productivity, m is the optimal team size, for the scenario of homogeneous team sizes and homogeneous workforce, if:

$$\frac{G_{m+1}-G_m}{L_{m+1}G_{m+1}-L_m G_m} < \delta < \frac{G_m-G_{m-1}}{L_m G_m-L_{m-1}G_{m-1}} \quad \forall\, m \tag{4.7}$$

for homogeneous systems composed of multiple additive tasks.

Theorem 1 states that when the objective is to maximize system productivity, when considering the case where no difference is assumed in workers productivity and workforce should be grouped in teams of equal size, the optimal team size can be determined by equation 4.7 for production systems composed of multiple additive tasks. Homogeneous systems are defined in this work as systems composed of one task type.

A limitation of the current expression is that it does not eliminate infeasible solutions. For example, the described case when considering homogeneous team sizes, meaning for homogeneous team sizes that each team created in the system must have assigned the same number of workers to perform each task, must only consider teams of size m for which the number of workers in the workforce be divisible for it. For example, for a workforce composed of 10 workers, forming teams of size m=3, meaning assigning three workers in each team, is not feasible. The division of the workforce (W=10) by the team size (m=3) returns a value that is not an integer value, therefore teams of size 3 for a workforce composed of 10 workers must not be treated as a feasible solution. Thus, for this problem the user can evaluate for example team sizes m = 2, 5, or 10. For the case of evaluating a team size m=2, (m-1) will take the value of 1 which is the next lower feasible team size from the team size of interest m=2, and (m+1) will take a value of 5 which is the next higher feasible team size from the team size of interest m=2.

Therefore, the user must consider this assumption when applying the mathematical expression presented in Theorem 1 to determine the optimal team size. This can be done dividing the total workforce (W) by the team size (m). If this ratio is a positive integer value, then the solution is feasible, and the user can proceed to apply the formulation to determine the optimal team size.

Proof Theorem 1: Homogeneous Workforce – Homogeneous Team Size for Case I) Additive Task Type

When considering a homogeneous workforce, equation 4.3 is simplified to equation 4.8. For this case the performance of workers is not going to differ within the workforce. Assuming constant values for parameters k, p, and r, variations in workers' productivity are obtained only along changes in team size m.

$$F(m) = k(1 - \delta L_m)\left(\frac{r}{1+\theta(m-1)} e^{-\left(\frac{x+\theta x(m-1)+p}{r}\right)} + x\right)\Big|_a^b \tag{4.8}$$

Then, for a production system composed of multiple additive tasks considering homogeneous team size and a fixed homogeneous workforce composed of *W* workers the system output is defined in equation 4.9. In this scenario each task is assigned to a team of equal size, meaning that every team have equal number of workers to perform the task over a specific time horizon. For additive tasks, the team performance is defined by summation of the individual contribution of members within the team. The system performance then is defined as the sum of teams' output, assuming independency between tasks in the system.

$$S_m = Wk(1 - \delta L_m)\left(\frac{r}{1+\theta(m-1)} e^{-\left(\frac{x+\theta x(m-1)+p}{r}\right)} + x\right)\Big|_a^b \tag{4.9}$$

Thus, equation 4.9 which represents system output can be rewrite (equation 4.10) using function G_m previously defined in equation 4.5.

$$S_m = Wk(1 - \delta L_m)G_m \tag{4.10}$$

Then, for a production system composed of multiple additive task considering a homogeneous workforce and homogeneous team sizes, a team size m_1 is preferred to a team size m_2, if the system output considering an arrangement of the workers in teams of size m_1 is greater than the system output when workers are arranged in teams of size m_2, meaning $S_{m_1} > S_{m_2}$. This relationship has been established in equation 4.11.

$$kW\left(1 - \delta L_{m_1}\right)G_{m_1} > kW\left(1 - \delta L_{m_2}\right)G_{m_2} \tag{4.11}$$

For this scenario the value of parameter *k* which represents the individual steady state productivity and parameter *W* which represents the number of workers that composed the workforce, are constant and fixed values across all workers in the workforce and all considered team sizes. Therefore, equation 4.11 is simplified to:

$$\left(1 - \delta L_{m_1}\right)G_{m_1} > \left(1 - \delta L_{m_2}\right)G_{m_2} \tag{4.12}$$

Solving equation 4.12 for the parameter δ, which represents the degree of process loss faced in a work setting, a team size m_1 is preferred to a team size m_2, if:

$$\delta > \frac{G_{m_2} - G_{m_1}}{L_{m_2} G_{m_2} - L_{m_1} G_{m_1}} \tag{4.13}$$

Given that function 4.9 have no more than one maximum point (Appendix A), it is concluded that *m* is the optimal team size if:

$$\frac{G_{m+1} - G_m}{L_{m+1} G_{m+1} - L_m G_m} < \delta < \frac{G_m - G_{m-1}}{L_m G_m - L_{m-1} G_{m-1}} \qquad \forall\, m \in M \tag{4.14}$$

Case II) Conjunctive Task Type

This case considers a production system composed of multiple *conjunctive* tasks. A conjunctive task has been defined as a task in which every member in the team needs to develop a part of the task in order to achieve the task's completion. Conjunctive tasks consist of a series of elements which are dependent within the task and that need to be complete in their totality in order to complete the task. For the considered case in this work, we consider a production system with a fixed constant workforce composed of *W* workers and *W/m* homogeneous conjunctive tasks. Each task has assigned one team and all teams in the system have equal number of workers to perform the task. Each worker within the team have assigned a task element. The performance of the team in a conjunctive task setting is determined by the least competent member (Steiner 1972).

Theorem 1 has been extended to production systems composed of multiple conjunctive tasks, when considering a homogeneous workforce and homogeneous team sizes within the system. For this case system output is defined by the sum of the individual output of teams. As described above, teams' output is determined by the individual output of the least competent member given the dependent relationship between task elements which defines conjunctive tasks. Therefore, when maximizing system productivity, with a performance model that considers the effect of experience, knowledge transfer and process loss to estimate individual workers productivity, *m* is the optimal team size, for the scenario of homogeneous team sizes and homogeneous workforce, if:

$$\frac{mG_{m+1} - (m+1)G_m}{mL_{m+1} G_{m+1} - (m+1) L_m G_m} < \delta < \frac{(m-1)G_m - mG_{m-1}}{(m-1) L_m G_m - mL_{m-1} G_{m-1}} \qquad \forall\, m \tag{4.15}$$

for homogeneous systems composed multiple conjunctive tasks. When the objective is to maximize system productivity, considering the case where no difference is assumed in workers productivity and workforce is grouped in teams of equal size, the optimal team size can be determined by equation 4.15 for production systems composed of multiple conjunctive tasks. Homogeneous systems are defined in this work as systems composed of one task type.

Proof Extension Theorem 1: Homogeneous Workforce – Homogeneous Team Size for Case II) Conjunctive Task Type

For a production system composed of multiple conjunctive tasks considering homogeneous team sizes and a homogeneous workforce composed of *W* workers, the system output is defined in equation 4.16. In this scenario each task is assigned to a team of equal size, meaning that every team have equal number of workers to perform the task over a specific time horizon, in our case [*a*,*b*]. For conjunctive tasks, the team performance is defined by the least competent member in the team. The system performance is defined as the sum of teams' output, assuming independency between tasks in the system.

For the case of homogeneous workforce, no difference between workers is considered. Then, the performance of the least competent member of each team is defined by equation 4.6. The system performance for a production system composed of *W/m* conjunctive tasks when considering a homogeneous workforce and homogeneous team sizes is defined by equation 4.16.

$$S_m = \frac{Wk(1-\delta L_m)}{m}\left(\frac{r}{1+\theta(m-1)}e^{-\left(\frac{x+\theta x(m-1)+p}{r}\right)} + x\right)\Bigg|_a^b \tag{4.16}$$

Considering the definition of the function G_m of equation 4.5, the expression for system output can be rewrite as equation 4.17.

$$S_m = \frac{Wk(1-\delta L_m)G_m}{m} \tag{4.17}$$

Therefore, for a production system composed of multiple conjunctive tasks considering a homogeneous workforce and homogeneous team sizes, a team size m_1 is preferred to a team size m_2, if the system output considering an arrangement of the workers in teams of size m_1 is greater than the system output when workers are assigned in teams of size m_2, meaning $S_{m_1} > S_{m_2}$.

$$\frac{Wk(1-\delta L_{m_1})G_{m_1}}{m_1} > \frac{Wk(1-\delta L_{m_2})G_{m_2}}{m_2} \tag{4.18}$$

Assuming a fixed homogeneous workforce the parameter W takes the same value on both sides of equation 4.18. Thus, equation 4.18 is simplified as:

$$\frac{k(1-\delta L_{m_1})G_{m_1}}{m_1} > \frac{k(1-\delta L_{m_2})G_{m_2}}{m_2} \tag{4.19}$$

Solving equation 4.19 for the parameter δ, which represents the degree of process loss faced in a specific work setting, a team size m_1 is preferred to a team size m_2 if:

$$\delta > \frac{m_1 G_{m2} - m_2 G_{m1}}{m_1 L_2 G_{m2} - m_2 L_1 G_{m1}} \tag{4.20}$$

Therefore, given that function 4.16 have no more than one maximum point (Appendix A), it is concluded that m is the optimal team size of a production systems consisting of multiple conjunctive tasks if:

$$\frac{mG_{m+1}-(m+1)G_m}{mL_{m+1}G_{m+1}-(m+1)L_m G_m} < \delta < \frac{(m-1)G_m - mG_{m-1}}{(m-1)L_m G_m - mL_{m-1}G_{m-1}} \quad \forall\, m \in M \tag{4.21}$$

when considering a homogeneous fixed workforce and homogeneous team sizes.

Case III) Disjunctive Task Type

Case III considers a production system composed of multiple *disjunctive* tasks. Disjunctive tasks represent indivisible tasks, where the team needs to complete the task together as a single problem. A disjunctive task can be found in settings where projects are assigned as a single-indivisible unit that needs to be completed by a team. For the considered case in this work, we consider a production system with a fixed constant workforce composed of *W* workers and *W/m* homogeneous disjunctive tasks. Each task has assigned one team and all teams in the system have equal number of workers to perform the task. Every group of workers assigned in a team have assigned one indivisible task that needs to be completed during a specific time horizon, which for this case have been defined as [*a*,*b*]. The performance of the team in a disjunctive task setting is determined by the most competent member (Steiner 1972).

Theorem 1 has been extended to production systems composed of multiple disjunctive tasks, when considering a homogeneous workforce and homogeneous team sizes within the system. For this scenario when considering a homogeneous workforce, no difference is obtained in workers performances within a team. That means, that in the team there is not a least or most competent member given that all workers are considered equally competent in terms of their individual productivity. Therefore, when maximizing system productivity, with a performance model that considers the effect of experience, knowledge transfer and process loss to estimate individual workers productivity, the optimal team size for the scenario of homogeneous team sizes and homogeneous workforce can be determined by equation 4.15 for homogeneous systems composed multiple disjunctive tasks.

When the objective is to maximize system productivity, considering the case where no difference is assumed in workers productivity and workforce is grouped in teams of equal size, the optimal team size can be determined by equation 4.15 for production systems composed of multiple disjunctive tasks.

Proof Extension Theorem 1: Homogeneous Workforce – Homogeneous Team Size for Case III) Disjunctive Task Type

For this case is considered a production system composed of multiple disjunctive tasks with homogeneous team sizes and a homogeneous workforce composed of *W* workers. Similar than in previous cases, this scenario assumes that a production system can be divided in tasks, and each task in the system is assigned to a team of equal size. The system performance is defined as the sum of teams' output, assuming independency between tasks in the system, wherein for disjunctive tasks, team performance is defined by the most competent member in the team.

For the case of homogeneous workforce, no difference between workers is considered. Then, the performance of the most competent member of each team for the time horizon [*a,b*] is defined by equation 4.6. Then, for a production system comprising a fixed workforce of *W* workers, wherein workers are assigned in teams of size *m*, the system output is going to be composed of *W/m* homogeneous teams' performances as presented in equation 4.16. Consequently, equation 4.15 hold for the scenario of a production system composed of multiple disjunctive tasks considering and homogeneous workforce and homogeneous teams' sizes.

Homogeneous Team Size – Heterogeneous Workforce

The presented cases referring to Theorem 1 addressed the scenario where all workers are identical with respect to their production rate capacity. However, realistically workforce is a heterogeneous resource, meaning that workers are going to have different learning rates and consequently different production rates. Although the consideration of the workforce as a homogeneous resource is a common assumption in problems related to operation management and optimization of production systems, the consideration of workforce heterogeneity and consequently the development of appropriate workforce management plans are critical aspects of production systems performance. Then, we extend Theorem 1 to the scenario of a production systems considering homogeneous team sizes and a heterogeneous workforce. This scenario addresses the case where differences between workers are considered with respect to their productivity and learning capacity. That means that for this scenario is accounted that each worker has a different learning capacity with respect to their experience and as consequence a different productivity rate over each unit of experience that is acquired. Then, for this scenario, the workers productivity outputs for a fixed time horizon [*a,b*] are estimated using equation 4.3.

For this problem, a function $Z_i(m)$ is defined in equation 4.22, which capture a fraction of the total productivity of worker *i* assigned to a team of size *m* during the time horizon [*a,b*], wherein function $Z_i(m)$ has been referred as $Z_{i,m}$ for simplification of the notation in following expressions. $Z_{i,m}$ has been defined in order to rewrite the expression to calculate the system output corresponding to each of the task types considered in this work.

$$Z_{i,m} = k_i \left(\frac{r_i}{1+\theta(m-1)} e^{-\left(\frac{x+\theta x(m-1)+p_i}{r_i}\right)} + x \right) \Bigg|_a^b \quad \forall\, i \in I \tag{4.22}$$

Therefore, equation 4.3 which defines the individual productivity output during a time horizon [a,b] for a worker i is rewrite as:

$$F_i(m) = k_i(1 - \delta L_m) Z_{i,m} \Big|_a^b \qquad \forall\, i \in I \tag{4.23}$$

Three different cases of production systems are considered for the scenario of homogeneous team sizes and heterogeneous workforce: Case I. additive tasks type, Case II. conjunctive task type, and Case III. disjunctive tasks type. The production systems considered in this work consists of a homogeneous structure, meaning that production systems evaluated in each case are composed of only one task type. The scope of this work does not extend to the analysis of hybrid production systems composed of multiple task types.

The mathematical expression to determine the optimal team size for this scenario for each of the listed cases is presented below.

Case I) Additive Task Type

This scenario addresses the case of a production systems composed of multiple additive tasks. Workforce heterogeneity and homogeneous team sizes are considered as part of this case. That means, that the production system is going to be divided in tasks that are categorized as additive task type and each task is assigned to a team with an equal number of workers within the team. Workers in this case are going to have different learning parameters and consequently different productivity rates, defining individual productivity rate with the expression presented in equation 4.23.

For additive tasks the team output is defined by the summation of the individual total outputs of the workers that composed the team during the time horizon [a,b]. The system output as previously defined in this work is obtained though the summation of teams' outputs, considering that tasks between teams are independent. Then, Theorem 1 has been extended to the scenario of a production system considering homogeneous team sizes and a heterogeneous workforce, wherein the production system is composed of the sum of *W/m* additive tasks. As an extension of theorem 1 for this case, the optimal team size is determined by equation 4.24 based on the degree of process loss faced in the environment of interest.

When maximizing system productivity, with a performance model that considers the effect of experience, knowledge transfer and process loss to estimate individual workers productivity, m is the optimal team size for the scenario of homogeneous team sizes and heterogeneous workforce, if:

$$\frac{\sum_{i=1}^{n} z_{i,m+1} - \sum_{i=1}^{n} z_{i,m}}{L_{m+1}\sum_{i=1}^{n} z_{i,m+1} - L_m \sum_{i=1}^{n} z_{i,m}} < \delta < \frac{\sum_{i=1}^{n} z_{i,m} - \sum_{i=1}^{n} z_{i,m-1}}{L_m \sum_{i=1}^{n} z_{i,m} - L_{m-1}\sum_{i=1}^{n} z_{i,m-1}} \forall\, m,\ \forall\, i \qquad (4.24)$$

for homogeneous systems composed multiple additive tasks. When the objective is to maximize system productivity, considering the heterogeneity in workers productivity and considering that the workforce is grouped in teams of equal size, the optimal team size can be determined by equation 4.24 for production systems composed of multiple additive tasks.

The application of theorem 1 can be used as an intermediate step to simplify and solve additional problems such as the worker assignment problem or the scheduling problem for systems wherein the user wants to consider a team-based assignation policy (refers to Appendix B for an illustrative example).

Proof Extension Theorem 1: Heterogeneous Workforce – Homogeneous Team Size for Case I) Additive Task Type

When considering a heterogeneous workforce, individual workers productivity is defined by equation 4.1. Through the integration of equation 4.1 with respect to the variable x is obtained the expression to estimate the output of worker i for the time horizon [a,b] for this case (equation 4.3). Then, for this case variations in workers' productivity and consequently in workers total output for the fixed time horizon [a,b] are obtained across changes in team size m and as well across differences in learning parameters.

For a production system composed of multiple additive tasks considering homogeneous team size and a fixed heterogenous workforce composed of W workers the system output is defined in equation 4.25. In this scenario, in an instance considering a team size m, each task is assigned to a team, where every team in the system corresponding to the specific instance have equal number of workers to perform the task over the time horizon $[a,b]$. As previously defined, for additive tasks, the team performance is defined by summation of the individual contribution of members within the team. Then, consistently with our previous definition of system output equation 4.25 has been obtained though the summation of individual workers contribution to the team performance, defined in produced units for a time horizon $[a,b]$, and consequently to the total system output.

$$S_m = \sum_{i=1}^{n} k_i(1-\delta L_m)\left(\frac{r_i}{1+\theta(m-1)}e^{-\left(\frac{x+\theta x(m-1)+p_i}{r_i}\right)}+x\right)\Bigg|_a^b \tag{4.25}$$

Thus, equation 4.25 which represents system output can be rewrite in equation 4.26 using defined functions $Z_{i,m}$ and L_m.

$$S_m = (1-\delta L_m)\sum_{i=1}^{n} Z_{i,m} \tag{4.26}$$

For a production system composed of multiple additive task considering a heterogeneous workforce and homogeneous team sizes within the considered instance, a team size m_1 is preferred to a team size m_2, if the system output when grouping workers in teams of size m_1 is greater than the system output when grouping workers in teams of size m_2, meaning $S_{m_1} > S_{m_2}$. This relationship is expressed in equation 4.27.

$$\left(1-\delta L_{m_1}\right)\sum_{i=1}^{n} Z_{i,m_1} > \left(1-\delta L_{m_2}\right)\sum_{i=1}^{n} Z_{i,m_2} \tag{4.27}$$

Solving equation 4.27 for the parameter δ, a team size m_1 is preferred to a team size m_2 if:

$$\delta > \frac{\sum_{i=1}^{n} Z_{i,m_2} - \sum_{i=1}^{n} Z_{i,m_1}}{L_2\sum_{i=1}^{n} Z_{i,m_2} - L_1 Z_{i,m_1}} \tag{4.28}$$

Given that function 4.25 have no more than one maximum point (Appendix A), it is concluded that m is the optimal team size if:

$$\frac{\sum_{i=1}^{n} z_{i,m+1} - \sum_{i=1}^{n} z_{i,m}}{L_{m+1}\sum_{i=1}^{n} z_{i,m+1} - L_m \sum_{i=1}^{n} z_{i,m}} < \delta < \frac{\sum_{i=1}^{n} z_{i,m} - \sum_{i=1}^{n} z_{i,m-1}}{L_m \sum_{i=1}^{n} z_{i,m} - L_{m-1}\sum_{i=1}^{n} z_{i,m-1}} \ \forall\, m, \forall\, i \quad (4.29)$$

Case II) Conjunctive Task Type

This scenario considers a production system composed of multiple conjunctive tasks, each task assigned to a team of equal size *m*, meaning that every team have equal number of workers to perform the task over a specific time horizon. A fixed heterogeneous workforce is considered as well as part of this case. That means that workers are going to have different learning parameters and consequently different productivity rates, defining individual productivity rate with the expression presented in equation 4.1. Then, through the integration of equation 4.1, the total production output of worker *i* for the time horizon [*a*,*b*] is defined in equation 4.3.

In conjunctive tasks, the team performance is defined by the least competent member in the team. Therefore, the team output is defined by the performance of the least capable member, in this study represented by the worker with lower total production output over the time horizon [*a*,*b*]. The team's outputs are used to calculate system output, which consist of the summation of the individual team outputs as previously defined. That means, that the production system considered in this work assumed that tasks between teams in the system are independent. We used this assumption across all instances evaluated in this work.

For the definition of the expression to calculate system output, a new set of values $Q_{(j),m}$ is defined, containing the ascending sorted values of the individual outputs $F_i(m)$, equation 4.3, for $i \in I$ for a specific team size *m*, wherein $j=1 \ldots n$ and $m=1 \ldots s$. That means, that $Q_{1,m}$ represents the minimum value of worker productivity within the considered workforce (min$\{F_i(m)\}$ for all $i \in I$, $m \in M$) for a considered team size *m*, while $Q_{n,m}$ represents the maximum value of worker productivity (max$\{F_i(m)\}$ for all $i \in I$, $m \in M$) in the workforce for the specific team size *m*. For the construction of set $Q_{(j),m}$ the values of $F_i(m)$ are calculated a priori for the team size of interest. The set of values $Q_{(j),m}$ have been defined to account for the optimal assignment of workers when having heterogeneous workforce, wherein workers are distributed through *W/m* teams of size *m* in the system composed of multiple conjunctive tasks. Based on the set $Q_{(j),m}$, a parameter $Z_{j,m}$ is defined (equation 4.30) which represents a fraction of the individual productivity for worker *i* assigned to a team of size *m* during the time horizon [*a*,*b*]. $Z_{j,m}$ has been defined to simplify the expression of system output which is presented below in this work.

$$Z_{j,m} = k_j \left(\frac{r_j}{1+\theta(m-1)} e^{-\left(\frac{x+\theta x(m-1)+p_j}{r_j}\right)} + x \right) \Bigg|_a^b \tag{4.30}$$

Thus, using equation 4.30 in addition of the definition of system output presented in this work for the production system composed of multiple conjunctive tasks, Theorem 1 is extended to obtain the optimal team size for this case through the expression presented in equation 4.31. When maximizing system productivity, with a performance model that considers the effect of experience, knowledge transfer and process loss to estimate individual workers productivity, *m* is the optimal team size for the scenario of homogeneous team sizes and heterogeneous workforce, if:

$$\frac{\left[Z_{1,m+1}+\sum_{c=1}^{W/m+1} Z_{c+(m+1),m+1}\right]-\left[Z_{1,m}+\sum_{c=1}^{W/m} Z_{c+m,m}\right]}{L_{m+1}\left[Z_{1,m+1}+\sum_{c=1}^{W/m+1} Z_{c+(m+1),m+1}\right]-L_m\left[Z_{1,m}+\sum_{c=1}^{W/m} Z_{c+m,m}\right]} < \delta <$$

$$\frac{\left[Z_{1,m}+\sum_{c=1}^{W/m} Z_{c+m,m}\right]-\left[Z_{1,m-1}+\sum_{c=1}^{W/m-1} Z_{c+(m-1),m-1}\right]}{L_m\left[Z_{1,s}+\sum_{c=1}^{W/m} Z_{c+m,m}\right]-L_{m-1}\left[Z_{1,m-1}+\sum_{c=1}^{W/m-1} Z_{c+(m-1),m-1}\right]} \quad \forall\, m \in M \tag{4.31}$$

for homogeneous systems composed of multiple conjunctive tasks. When the objective is to maximize system productivity, considering workforce heterogeneity and equal size for team formation, the optimal team size can be determined by equation 4.31 for production systems composed of multiple conjunctive tasks.

Proof Extension Theorem 1: Heterogeneous Workforce – Homogeneous Team Size for Case II) Conjunctive Task Type

When considering a heterogeneous workforce, individual workers productivity is defined by equation 4.1. Therefore, for a fixed time horizon [a,b] the individual worker output considering individual learning parameters, shown in equation 4.3, is obtained through the integration of equation 4.1 with respect to the variable x. Then, variations in workers' productivity and consequently in workers total output for the time horizon [a,b] are obtained across changes in team size m and along differences in workers.

Team performance in a conjunctive task is defined by the least competent member in the team. In this study, we define team performance as team output. Thus, by the definition of team performance for conjunctive tasks, team output is going to be determined by the worker with lower productivity in a team over the time horizon [a,b] as expressed in equation 4.32. For a specific team of size m, meaning that m workers are working together in a conjunctive task as a team, the team output (C_m) is calculated in equation 4.32 as the minimum value of individual total output found within the group of workers composing a team.

$$C_m = \min\{F_{1,m} \dots F_{m,m}\} \tag{4.32}$$

Therefore, for a production system composed of multiple conjunctive tasks considering homogeneous team sizes and a fixed heterogenous workforce composed of W workers the system output is defined by the summation of the output of the less productive worker in each team that composed the system during the time horizon [a,b]. In this scenario, in an instance considering a team size m, each task is assigned to a team, where every team in the system corresponding to the specific instance have equal number of workers to perform the task.

To obtain the output of the multiple teams in the production system composed of conjunctive tasks while considering the optimal grouping of W workers in teams of size m, a new set of values $Q_{(j),m}$ is defined which contains the ascending sorted values of the variable $F_{i,m}$ (equation 4.3) which has been calculated a priori for the team size of interest, wherein $j=1 \dots n$ and $m=1 \dots s$. For this new set, $Q_{1,m}$ represents the minimum value of worker productivity within the considered workforce (min{$F_{i,m}$} for all $i \in I$, $m \in M$) for a considered team size m, while $Q_{n,m}$ represents the maximum value of worker productivity (max{$F_{i,m}$} for all $i \in I$, $m \in M$) in the workforce for the specific team size m. For this scenario a new parameter $Z_{j,m}$ is defined based on the set $Q_{(j),m}$ in order to capture a fraction of individual worker productivity and simplify the expression of system output later presented. Equation 4.33 shows the definition of the variable $Z_{j,m}$, wherein the index j corresponds to the sorting process of workers' productivity previously defined in the set $Q_{(j),m}$. Then, the values of the set $Q_{(j),m}$ can be rewrite in the equation 4.34 in terms of $Z_{j,m}$.

$$Z_{j,m} = k_j \left(\frac{r_j}{1+\theta(m-1)} e^{-\left(\frac{x+\theta x(m-1)+p_j}{r_j}\right)} + x \right) \Bigg|_a^b \quad \forall j \in J, \forall m \in M \quad (4.33)$$

$$Q_{(j),m} = (1 - L_m\delta) Z_{j,m} \quad \forall j \in J, \forall m \in M \quad (4.34)$$

For a system composed of *W/m* conjunctive tasks, wherein the output of each team is defined by the worker with lower productivity in each team, the optimal assignment of workers is obtained by creating homogeneous teams with respect to total workers production output. For example, considering a production system composed of three conjunctive tasks and a workforce composed of six workers. The optimal assignment of workers, considering the total system output as the performance measure, is obtained assigning the two workers with lowest productivity outputs in one team, the two subsequent worker in terms of total production output in the second team, and the two workers with highest total production outputs in the third team. This calculation has been introduced in the presented expression of theorem 1 for this case by the definition of the set $Q_{(j),m}$ in addition of a counter c that is introduced and discussed as part of equation 4.35.

Based on our previous definition of the production system which considers that tasks <u>*between*</u> teams are independent, the total output of the system is defined as the summation of teams outputs for all teams composing the production system, for the time horizon [a,b] as presented in equation 4.35.

$$S_m = (1 - \delta L_m)[Z_{1,m} + \sum_{c=1}^{\frac{W}{m}} Z_{c+m,m}] \quad \forall\, m \in M \tag{4.35}$$

An index *c* has been defined as a counter in order to capture output of teams as function of less productive worker of each team considering the optimal grouping of W workers in teams of size *m*.

Therefore, for a production system composed of multiple conjunctive tasks considering a heterogeneous workforce and homogeneous team sizes, a team size m_1 is preferred to a team size m_2 if $S_{m_1} > S_{m_2}$. That means, grouping workers in teams of size m_1 is preferred to grouping workers in teams of size m_2 if the system output when considering an arrangement of the workers in teams of size m_1 is greater than the system output considering teams of size m_2. This relationship has been expressed in equation 4.36.

$$\left(1 - \delta L_{m_1}\right)[Z_{1,m_1} + \sum_{c=1}^{\frac{W}{m_1}} Z_{c+m_1,m_1}] > \left(1 - \delta L_{m_2}\right)[Z_{1,m_2} + \sum_{c=1}^{\frac{W}{m_2}} Z_{c+m_2,m_2}] \tag{4.36}$$

Solving equation 4.36 for the parameter δ, a team size m_1 is preferred to a team size m_2 if:

$$\delta > \frac{\left[Z_{1,m_2} + \sum_{c=1}^{W/m_2} Z_{c+m_2,m_2}\right] - \left[Z_{1,m_1} + \sum_{c=1}^{W/m_1} Z_{c+m_1,m_1}\right]}{L_{m_2}\left[Z_{1,m_2} + \sum_{c=1}^{W/m_2} Z_{c+m_2,m_2}\right] - L_{m_1}\left[Z_{1,m_1} + \sum_{c=1}^{W/m_1} Z_{c+m_1,m_1}\right]} \tag{4.37}$$

Given that function 4.35 have no more than one maximum point (Appendix A), it is concluded that *m* is the optimal team size if:

$$\frac{\left[Z_{1,m+1} + \sum_{c=1}^{W/m+1} Z_{c+(m+1),m+1}\right] - \left[Z_{1,m} + \sum_{c=1}^{W/m} Z_{c+m,m}\right]}{L_{m+1}\left[Z_{1,m+1} + \sum_{c=1}^{W/m+1} Z_{c+(m+1),m+1}\right] - L_m\left[Z_{1,m} + \sum_{c=1}^{W/m} Z_{c+m,m}\right]} < \delta <$$

$$\frac{\left[Z_{1,m} + \sum_{c=1}^{W/m} Z_{c+m,m}\right] - \left[Z_{1,m-1} + \sum_{c=1}^{W/m-1} Z_{c+(m-1),m-1}\right]}{L_m\left[Z_{1,s} + \sum_{c=1}^{W/m} Z_{c+m,m}\right] - L_{m-1}\left[Z_{1,m-1} + \sum_{c=1}^{W/m-1} Z_{c+(m-1),m-1}\right]} \quad \forall\, m \in M \tag{4.38}$$

Case III) Disjunctive Task Type

In this case a production system composed of multiple disjunctive tasks is considered, where each task is assigned to one team, and considering that every team have equal number of workers to perform the task. Workforce heterogeneity is considered in this case, meaning that workers are going to have different productivity rates, defining individual productivity rate with the expression presented in equation 4.1. Through the integration of equation 4.1 with respect to the variable *x*, the total output of worker *i* for the time horizon [*a*,*b*] is obtained as defined in equation 4.3.

For disjunctive tasks the performance of a team is defined by the most competent member in the team. Therefore, the team output is defined by the performance of the most competent member, in this study represented by the worker with higher total production output for the time horizon [*a*,*b*]. The team's outputs are used to calculate system output, which consist of the summation of the individual team outputs as previously defined, meaning that the production system assumed independence between tasks assigned to the different teams in the system.

Similar than for the case of conjunctive tasks, in order to calculate system output, a new set of values $B_{(j),m}$ is defined, containing the descending sorted values of the individual outputs $F_i(m)$, equation 4.3, for $i \in I$ for a specific team size *m*, wherein *j=1…n* and *m=1…s*. That means, that $B_{1,m}$ represents the maximum value of worker productivity within the considered workforce (max$\{F_i(m)\}$ for all $i \in I$, $m \in M$) for a considered team size *m*, while $B_{n,m}$ represents the minimum value of worker productivity (min$\{F_i(m)\}$ for all $i \in I$, $m \in M$) in the workforce for the specific team size *m*. For the construction of set $B_{(j),m}$ the values of $F_i(m)$ are calculated a priori for the team size of interest. The set of values $B_{(j),m}$ have been defined to account for the optimal assignment of workers when having heterogeneous workforce, wherein workers are distributed through *W/m* teams of size *m* in the system composed of multiple disjunctive tasks. Based on the set $B_{(j),m}$, a parameter $Z_{j,m}$ is defined (equation 4.39) which represents a fraction of the individual productivity for worker *i* assigned to a team of size m during the time horizon $[a,b]$. $Z_{j,m}$ has been defined to simplify the expression of system output which is presented below in this work.

$$Z_{j,m} = k_j \left(\frac{r_j}{1+\theta(m-1)} e^{-\left(\frac{x+\theta x(m-1)+p_j}{r_j}\right)} + x \right) \Bigg|_a^b \quad \forall j \in J,\ \forall m \in M \qquad (4.39)$$

Therefore, Theorem 1 is extended to obtain the optimal team size for the case of a production system composed of multiple disjunctive tasks considering homogeneous team sizes and a heterogeneous workforce through the expression presented in equation 4.40. with a performance model that considers the effect of experience, knowledge transfer and process loss to estimate individual workers productivity, m is the optimal team size for the scenario of homogeneous team sizes and heterogeneous workforce, if:

$$\frac{\left[\sum_{j=1}^{W/m+1} Z_{j,m+1}\right] - \left[\sum_{j=1}^{W/m} Z_{j,m}\right]}{L_{m+1}\left[\sum_{j=1}^{W/m+1} Z_{j,m+1}\right] - L_m\left[\sum_{j=1}^{W/m} Z_{j,m}\right]} < \delta <$$

$$\frac{\left[\sum_{j=1}^{\frac{W}{m}} Z_{j,m}\right] - \left[\sum_{j=1}^{\frac{W}{m-1}} Z_{j,m-1}\right]}{L_m\left[\sum_{j=1}^{\frac{W}{m}} Z_{j,m}\right] - L_{m-1}\left[\sum_{j=1}^{\frac{W}{m-1}} Z_{j,m-1}\right]} \quad \forall\, m \in M \qquad (4.40)$$

for homogeneous systems composed multiple disjunctive tasks. When the objective is to maximize system productivity, considering workforce heterogeneity and equal size for team formation, the optimal team size can be determined by equation 4.40 for production systems composed of multiple disjunctive tasks.

Proof Extension Theorem 1: Homogeneous Workforce – Homogeneous Team Size for Case III) Disjunctive Task Type

For this case, when considering a heterogeneous workforce, individual workers productivity is defined by equation 4.1. Therefore, for a fixed time horizon $[a,b]$ the individual worker output considering the effect of learning, knowledge transfer and process loss, is obtained through the integration of equation 4.1 with respect to the variable *x*. This expression for total individual worker output is obtained in equation 4.3. Then, variations in workers' productivity and consequently in workers total output for the time horizon [a,b] are obtained across changes in team size m and across variations of workers in the workforce.

The team performance in a disjunctive task is defined by the most competent member in the team. Defining team performance as team output, for disjunctive tasks the team performance is going to be determined by the worker with higher productivity over the time horizon [a,b] in a team (equation 4.41). For a specific team of size m, meaning that m workers are working together in a disjunctive task as a team, the team output (C_m) is calculated in equation 4.41 as the maximum value of individual total output found within the group of workers composing a team.

$$C_m = \max\{F_{1,m} \ldots F_{m,m}\} \tag{4.41}$$

Therefore, for a production system composed of multiple disjunctive tasks considering homogeneous team sizes and a fixed heterogenous workforce composed of W workers the system output is defined by the summation of the output of the most productive worker in each team that composed the system during the time horizon [a,b]. In this scenario, in an instance considering a team size m, each task is assigned to a team, where every team in the system corresponding to the specific instance have equal number of workers to perform the task.

To obtain the output of the multiple teams in the production system composed of disjunctive tasks while considering the optimal grouping of W workers in teams of size m, a new set of values $B_{(j),m}$ is defined which contains the descending sorted values of the variable $F_{i,m}$ (equation 4.3) which has been calculated a priori for the team size of interest, wherein $j=1 \ldots n$ and $m=1 \ldots s$. For this new set, $B_{1,m}$ represents the maximum value of worker total productivity within the considered workforce ($\max\{F_{i,m}\}$ for all $i \in I$, $m \in M$) for a considered team size m, while $B_{n,m}$ represents the minimum value of worker productivity ($\min\{F_{i,m}\}$ for all $i \in I$, $m \in M$) in the workforce for the specific team size m. For this scenario a new parameter $Z_{j,m}$ is defined based on the set $B_{(j),m}$ in order to capture a fraction of individual worker productivity and simplify the expression of system output later presented. Equation 4.42 shows the definition of the variable $Z_{j,m}$, wherein the index j corresponds to the sorting process of workers' productivity previously defined in the set $B_{(j),m}$. Then, the values of the set $B_{(j),m}$ can be rewrite in the equation 4.43 in terms of $Z_{j,m}$.

$$Z_{j,m} = k_j\left(\frac{r_j}{1+\theta(m-1)}e^{-\left(\frac{x+\theta x(m-1)+p_j}{r_j}\right)} + x\right)\Bigg|_a^b \quad \forall j \in J,\ \forall m \in M \quad (4.42)$$

$$B_{(j),m} = (1-\delta L_m)Z_{j,m} \quad \forall j \in J,\ \forall m \in M \quad (4.43)$$

For a system composed of *W/m* disjunctive tasks, wherein the output of each team is defined by the worker with highest total productivity in each team, the optimal assignment of workers is obtained by assigning the workers with highest total outputs into different teams. For example, considering a production system composed of three disjunctive tasks and a workforce composed of six workers. The optimal assignment of workers, considering the total system output as the performance measure, is obtained assigning the workers with highest productivity output in one team, the subsequent worker in terms of total production output in the second team, and the workers that is in the third position with respect to the highest total production output in the third team. This calculation has been introduced in the presented expression of Theorem 1 for this case by the definition of the set $B_{(j),m}$.

As previously defined the production system considered in this work assumes that tasks ***between*** teams are independent. Thus, the total output of the system is defined as the summation of teams outputs for all teams composing the production system, for the time horizon [a,b] as presented in equation 4.44.

$$S_m = (1-\delta L_m)[\textstyle\sum_{j=1}^{\frac{W}{m}} Z_{j,m}] \quad (4.44)$$

Therefore, for a production system composed of multiple disjunctive tasks considering a heterogeneous workforce and homogeneous team sizes, a team size m_1 is preferred to a team size m_2 if $S_{m_1} > S_{m_2}$. That means, grouping workers in teams of size m_1 is preferred to grouping workers in teams of size m_2 if the system output when considering an arrangement of the workers in teams of size m_1 is greater than the system output considering teams of size m_2. This relationship has been expressed in equation 4.45.

$$\left(1-\delta L_{m_1}\right)[\sum_{j=1}^{\frac{W}{m_1}} Z_{j,m_1}] > \left(1-\delta L_{m_2}\right)[\sum_{j=1}^{\frac{W}{m_2}} Z_{j,m_2}] \tag{4.45}$$

Solving equation 4.45 for the parameter δ, a team size m_1 is preferred to a team size m_2 if:

$$\delta > \frac{\left[\sum_{j=1}^{W/m_2} Z_{j,m_2}\right] - \left[\sum_{j=1}^{W/m_1} Z_{j,m_1}\right]}{L_{m_2}\left[\sum_{j=1}^{W/m_2} Z_{j,m_2}\right] - L_{m_1}\left[\sum_{j=1}^{W/m_1} Z_{j,m_1}\right]} \tag{4.46}$$

Given that function 4.44 have no more than one maximum point (Appendix A), it is concluded that *m* is the optimal team size if:

$$\frac{\left[\sum_{j=1}^{W/m+1} Z_{j,m+1}\right]-\left[\sum_{j=1}^{W/m} Z_{j,m}\right]}{L_{m+1}\left[\sum_{j=1}^{W/m+1} Z_{j,m+1}\right]-L_m\left[\sum_{j=1}^{W/m} Z_{j,m}\right]} < \delta < \frac{\left[\sum_{j=1}^{\frac{W}{m}} Z_{j,m}\right]-\left[\sum_{j=1}^{\frac{W}{m-1}} Z_{j,m-1}\right]}{L_m\left[\sum_{j=1}^{\frac{W}{m}} Z_{j,m}\right]-L_{m-1}\left[\sum_{j=1}^{\frac{W}{m-1}} Z_{j,m-1}\right]} \quad \forall\, m \in M$$

(4.47)

4.3.3 Illustrative Examples: Application of the Mathematical Expression for Solving the Team Sizing Problem.

This example illustrates how the team sizing problem can be addressed using the mathematical expression presented in Theorem 1 and the extensions for each considered scenario and task type. The example describes a production manufacturing environment comprising a workforce of 6 workers. The main goal addressed in this example is to determine the optimal team size for the described production system assuming the relationship between task in the system are independent and the relationship within the task is defined by the task type, additive conjunctive or disjunctive. The example considers a pure production system of only one type of task within the system, and homogeneous team size have been considered as a constraint. The productivity of the workers is modeled by the learning curve presented in equation 4.1. The results obtained from the application of the theorem in the example have been validated with simulation constructed in MATLAB from the described scenario. The description of the results is presented below.

Homogeneous Team Size – Homogeneous Workforce

The first scenario addressed in the illustrative example represents the case of homogeneous workforce and homogeneous team size. In this it is assumed that there is no difference between workers with respect to their learning capacity and productivity rate, and that all workers are assigned to teams of equal size. That means that all workers produce at the same rate, and same number of workers are assigned to every team that composed the system. The example described in this scenario considers a production manufacturing environment comprising a workforce of 6 workers with identical learning parameters and productivity rates. The productivity of the workers is modeled by the learning curve presented in equation 4.1. Table 4.1 describes the learning parameters used to determine the productivity rate of each workers for the illustrative example. For the purpose of the example a value of theta (θ) of 0.5 has been considered.

Table 4.1 Workers Learning Parameters for the scenario of Homogeneous Team Size- Homogeneous Workforce

Worker i (W_i)	k_i	p_i	r_i
W_1	12.82	135.78	84.45
W_2	12.82	135.78	84.45
W_3	12.82	135.78	84.45
W_4	12.82	135.78	84.45
W_5	12.82	135.78	84.45
W_6	12.82	135.78	84.45

For this scenario three different cases are evaluated, Case I) additive task type, Case II) conjunctive task type, and Case III) disjunctive task type. The results of the application of the theorem for each case are discussed below.

Case I) Additive Task Type

The production system evaluated in this case consist of a system composed of multiple *additive* tasks. An additive task has been defined as a task where the individual contributions of the team members are combined as a single output. Then, the team performance for additive tasks is determined by the sum of the individual contributions of all team members (Steiner 1972). In this work, team performance has been defined as the team total output through a time horizon of 50-time periods. System output is defined as the summation of teams' outputs, considering that tasks between teams are independent. Each task in the production system is assigned to one only team and vice versa.

Given the size of the workforce, 6 workers, and the assumptions of homogeneous team sizes, the feasible solutions for the problem presented in this example are teams of size (m) 1, 2, 3 or 6. We start evaluating a team size of one worker per team. That means, a single-based assignment policy is evaluated. Then for a team size of 1 (m=1) there is no adjacent lower value (m-1), therefore theorem 1 modify as illustrated below in equation 4.48. The adjacent higher value (m+1) of m=1 for this case is 2.

$$\frac{G_{m+1}-G_m}{L_{m+1}G_{m+1}-L_m G_m} < \delta \tag{4.48}$$

Therefore, using equation 4.5 the values of G_m and G_{m+1} are calculated (G_1 = 41.64, G_2= 42.56). The values for process loss are then obtained for each team size (L_m & L_{m+1}) using the expression L_m = -0.1 + 0.09m, wherein the value of process loss (L_m) for the team size =1 is zero. Thus, the expression 4.48 simplify as

$$\frac{G_{m+1}-G_m}{L_{m+1}G_{m+1}} < \delta \tag{4.49}$$

Then, the lower bound of the inequality presented in equation 4.49 is obtained (equation 4.50).

$$0.27 < \delta \tag{4.50}$$

For the result can be concluded that a team size of 1 worker per team is the optimal team size when having a degree of process loss higher than 0.27 in the described team sizing scenario, considering homogeneous team sizes, a homogeneous workforce comprising 6 identical workers, and a percentage of knowledge transfer between workers of 50% (θ=0.5). The results have been validated simulating different instances of process loss (δ) on MATLAB. The results of the simulation are presented in Table 4.2.

For the team size equal to 2 workers per team (m=2), the adjacent lower value (m-1) is equal to 1, while the adjacent higher value (m+1) is equal to 3. Therefore, using equation 4.5 the values of G_m, G_{m+1} and G_{m-1} are calculated (G_2 = 42.56, G_3= 43.33, and G_1 = 41.64). Using equation 4.47 the lower and upper values of δ are obtained for the team size of two workers per team.

$$0.19 \leq \delta \leq 0.27 \tag{4.51}$$

Through the result can be concluded that a team size of 2 worker per team is the optimal team size when having a degree of process loss higher than 0.19 and lower than 0.27 in the described team sizing scenario, considering homogeneous team sizes, a homogeneous workforce comprising 6 identical workers, and a percentage of knowledge transfer between workers of 50% (θ=0.5). The results have been validated simulating different instances of process loss (δ) on MATLAB as presented in Table 4.2. The calculations for the remaining team sizes are obtained in the same fashion. The results for the team size of three workers per team and six workers per team are presented in equation 4.52 and 4.53 respectively.

$$0.13 \leq \delta \leq 0.19 \tag{4.52}$$

$$\delta \leq 0.13 \tag{4.53}$$

Table 4.2 Results obtained from the simulation for different instances of δ for the production system composed of additive tasks – Homogeneous Workforce.

TS (workers/ team)	System Output (δ=0.15)	System Output (δ=0.20)	System Output (δ=0.25)	System Output (δ=0.35)	System Output (δ=0.5)	System Output (δ=0.75)
1	3268	3268	3268	**3268****	**3268****	**3268****
2	3300	**3286****	**1637****	3246	3206	3140
3	**3313****	3284	1085	3197	3111	2966
6	3295	3217	523	2984	2752	2364

Case II) Conjunctive Task Type

The production system evaluated in this case consist of a system composed of multiple *conjunctive* tasks. A conjunctive task has been defined as a task in which every member in the team needs to develop a part of the task in order to achieve the task's completion. Then, the team performance for conjunctive tasks is determined by the least competent member, in this example represented by the worker within the team with lower production output for the specified time horizon (Steiner 1972). System output then, is defined as the summation of teams' outputs, considering that tasks between teams are independent. Each task in the production system is assigned to one only team and vice versa.

Considering a workforce of 6 workers, and the assumptions of homogeneous team sizes, the feasible solutions for the problem presented in this example are teams of size (m) 1, 2, 3 or 6. We start evaluating a team size of one worker per team.

Using equation 4.5 the values of G_m for each team size (G_1 = 41.64, G_2= 42.56, G_3= 43.33, G_6= 44.97). The G_m values and the process loss are then obtained for each team size using the expression L_m = -0.1 + 0.09m, wherein the value of process loss (L_m) for the team size =1 is zero. For evaluating the team size equal to one worker per team the expression 4.15 is simplified as

$$\frac{mG_{m+1}-(m+1)G_m}{mL_{m+1}G_{m+1}-(m+1)L_mG_m} < \delta \tag{4.54}$$

Then, the lower bound of the inequality presented in equation 4.54 is obtained and presented in equation 4.55.

$$-9.60 < \delta \tag{4.55}$$

The level of δ is defined in a range of [0,1]. Therefore, equation 4.55 can be updated as

$$0 < \delta \tag{4.56}$$

From the result obtained for this case we can be concluded that a team size of 1 worker per team is the optimal team size consistently across all possible levels of degree of process loss, considering the defined range for possible values of δ and considering homogeneous team sizes, a homogeneous workforce comprising 6 identical workers, and a percentage of knowledge transfer between workers of 50% (θ=0.5). The results have been validated simulating different instances of process loss (δ) on MATLAB. The results of the simulation are presented in Table 4.3. Given that a team size of one worker per team have been found as the optimal team size across all possible scenarios of process loss (δ), then is no needed further exploration of others team sizes.

Table 4.3 Results obtained from the simulation for different instances of δ for the production system composed of conjunctive tasks – Homogeneous Workforce.

TS (workers/ team)	System Output (δ=0.15)	System Output (δ=0.20)	System Output (δ=0.25)	System Output (δ=0.35)	System Output (δ=0.5)	System Output (δ=0.75)
1	**3268****	**3268****	**3268****	**3268****	**3268****	**3268****
2	1650	1643	1637	1623	1603	1570
3	1104	1095	1085	1066	1037	989
6	549	536	523	497	459	394

Case III) Disjunctive Task Type

The production system evaluated in this case consist of a system composed of multiple *disjunctive* tasks. Disjunctive tasks represent indivisible tasks, where the team needs to complete the task together as a single problem. Then, the team performance for disjunctive tasks is determined by the most competent member, in this example represented by the worker within the team with higher production output for the specified time horizon (Steiner 1972). System output then, is defined as the summation of teams' outputs, considering that tasks between teams are independent. Each task in the production system is assigned to one only team and vice versa.

For this scenario represented by a homogeneous workforce, there is no difference in workers performances within a team. That means, that in the team there is not a least or most competent member given that all workers are considered equally competent in terms of their individual productivity. Therefore, when maximizing system productivity, with a performance model that considers the effect of experience, knowledge transfer and process loss to estimate individual workers productivity, the optimal team size for the scenario of homogeneous team sizes and homogeneous workforce can be determined by equation 4.15 for homogeneous systems composed multiple disjunctive tasks. Therefore, the results for the illustrative example of a production system composed of conjunctive tasks considering homogeneous team sizes and homogeneous workforce remains the same (Table 4.4) for this case of a production system composed of disjunctive tasks when considering homogeneous team sizes and homogeneous workforce.

Table 4.4 Results obtained from the simulation for different instances of δ for the production system composed of disjunctive tasks – Homogeneous Workforce.

TS (workers/ team)	System Output (δ=0.15)	System Output (δ=0.20)	System Output (δ=0.25)	System Output (δ=0.35)	System Output (δ=0.5)	System Output (δ=0.75)
1	**3268****	**3268****	**3268****	**3268****	**3268****	**3268****
2	1650	1643	1637	1623	1603	1570
3	1104	1095	1085	1066	1037	989
6	549	536	523	497	459	394

Homogeneous Team Size – Heterogeneous Workforce

The second scenario addressed in the illustrative example represents the case of heterogeneous workforce and homogeneous team size. In this scenario it is considered difference between workers with respect to their learning capacity and productivity rate. This scenario assumes that all workers are assigned to teams of equal size, meaning that same number of workers are assigned to every team that composed the system. The example described in this scenario considers a production manufacturing environment comprising a workforce of 6 workers with different learning parameters and productivity rates. The productivity of the workers is modeled by the learning curve presented in equation 4.1. Table 4.5 describes the learning parameters used to determine the productivity rate of each worker for the illustrative example. For the purpose of the example a value of theta (θ) of 0.5 has been considered.

Table 4.5 Workers Learning Parameters for the scenario of Homogeneous Team Size- Heterogeneous Workforce.

Worker *i* (W_i)	k_i	p_i	r_i
W_1	12.82	135.78	84.45
W_2	8.65	104.36	44.33
W_3	33.70	176.91	68.20
W_4	39.20	11.02	31.70
W_5	29.60	24.12	193.36
W_6	36.35	258.88	78.30

For this scenario three different cases are evaluated, Case I) additive task type, Case II) conjunctive task type, and Case III) disjunctive task type. The results of the application of the theorem for each case are discussed below.

Case I) Additive Task Type

In this case is addressed the problem of team sizing considering a production system composed of multiple additive tasks, when considering homogeneous team sizes and a heterogeneous workforce comprising 6 workers. As previously defined the team performance for additive tasks is determined by the sum of the individual contributions of all team members (Steiner 1972), wherein in this work, team performance has been defined as the team total output through a time horizon of 50-time periods. System output has been defined as the summation of teams' outputs, considering that tasks between teams are independent. Each task in the production system is assigned to one only team and vice versa.

Given the size of the workforce, 6 workers, and the assumptions of homogeneous team sizes, the feasible solutions for the problem presented in this example are teams of size (m) 1, 2, 3 or 6. We start evaluating a team size of one worker per team. Then, for a team size of 1 (m=1) there is no adjacent lower value (m-1), therefore theorem 1 modify as illustrated below in equation 4.57. The adjacent higher value (m+1) of m=1 for this case is 2.

$$\frac{\sum_{i=1}^{n} Z_{i,m+1} - \sum_{i=1}^{n} Z_{i,m}}{L_{m+1}\sum_{i=1}^{n} Z_{i,m+1} - L_m \sum_{i=1}^{n} Z_{i,m}} < \delta \qquad (4.57)$$

Therefore, using equation 4.22 the values of $Z_{i,m}$ are calculated and used to solve equation 4.57. The values for process loss for each team size m (L_m & L_{m+1}) are then obtained using the expression $L_m = -0.1 + 0.09m$, wherein the value of process loss (L_m) for the team size =1 is zero. Then, solving inequality 4.57 we obtain the lower bound for optimality conditions for a team sizing policy of one worker per team.

$$0.56 < \delta \qquad (4.58)$$

For the result can be concluded that a team size of 1 worker per team is the optimal team size when having a degree of process loss higher than 0.56 in the described team sizing scenario, considering homogeneous team sizes, a heterogeneous workforce comprising 6 workers, and a percentage of knowledge transfer between workers of 50% (θ=0.5). The results have been validated simulating different instances of process loss (δ) on MATLAB. The results of the simulation are presented in Table 4.6.

For the team size equal to 2 workers per team (m=2), the adjacent lower value (m-1) is equal to 1, while the adjacent higher value (m+1) is equal to 3. Therefore, using equation 4.22 the values of $Z_{i,m}$ are calculated. Then, using equation 4.24 the lower and upper values of δ are obtained for evaluating the team size of two workers per team.

$$0.35 \leq \delta \leq 0.56 \qquad (4.59)$$

Through the result can be concluded that a team size of 2 worker per team is the optimal team size when having a degree of process loss higher than 0.35 and lower than 0.56 in the described team sizing scenario, considering homogeneous team sizes, a heterogeneous workforce comprising 6 workers, and a percentage of knowledge transfer between workers of 50% (θ=0.5). The results have been validated simulating different instances of process loss (δ) on MATLAB as presented in Table 4.6.

The calculations for the remaining team sizes are obtained in the same fashion. The results for the team size of three workers per team and six workers per team are presented in equation 4.60 and 4.61 respectively.

$$0.21 \leq \delta \leq 0.35 \tag{4.60}$$

$$\delta \leq 0.21 \tag{4.61}$$

Table 4.6 Results obtained from the simulation for different instances of δ for the production system composed of additive tasks – Heterogeneous Workforce.

TS (workers/ team)	System Output (δ=0.15)	System Output (δ=0.20)	System Output (δ=0.25)	System Output (δ=0.35)	System Output (δ=0.5)	System Output (δ=0.75)
1	5924	5924	5924	5924	5924	**5924****
2	6123	6099	6074	**6024****	**5950****	5826
3	6238	6184	**6130****	6021	5858	5585
6	**6346****	**6197****	6047	5748	5300	4553

Case II) Conjunctive Task Type

In this case is addressed the problem of team sizing considering a production system composed of multiple conjunctive tasks, when considering homogeneous team sizes and a heterogeneous workforce comprising 6 workers. As previously defined the team performance for conjunctive tasks is determined by the least competent member within the team (Steiner 1972), wherein in this work, team performance has been defined as the worker with the minimum production output through a time horizon of 50-time periods. System output has been defined as the summation of teams' outputs, considering that tasks between teams are independent. Each task in the production system is assigned to one only team and vice versa.

Using equation 4.31 the different team sizes (m=1,2,3,6) have been evaluated to determine the optimality conditions respecting δ for the described example. For a team size of one worker per team equation 4.31 simplify as

$$-16.35 < \delta \tag{4.62}$$

The level of δ is defined in a range of [0,1]. Therefore, equation 4.62 can be updated as

$$0 < \delta \tag{4.63}$$

From the result obtained for this case we can be concluded that a team size of 1 worker per team is the optimal team size consistently across all possible levels of degree of process loss, considering the defined range for possible values of δ and considering homogeneous team sizes, a heterogeneous workforce comprising 6 workers, and a percentage of knowledge transfer between workers of 50% (θ=0.5). The results have been validated simulating different instances of process loss (δ) on MATLAB. The results of the simulation are presented in Table 4.7. Given that a team size of one worker per team have been found as the optimal team size across all possible scenarios of process loss (δ), then is no needed further exploration of others team sizes.

Table 4.7 Results obtained from the simulation for different instances of δ for the production system composed of conjunctive tasks – Heterogeneous Workforce.

TS (workers/ team)	System Output (δ=0.15)	System Output (δ=0.20)	System Output (δ=0.25)	System Output (δ=0.35)	System Output (δ=0.5)	System Output (δ=0.75)
1	**5924****	**5924****	**5924****	**5924****	**5924****	**5924****
2	2537	2526	2516	2496	2465	2413
3	1919	1903	1886	1852	1802	1718
6	395	385	376	358	330	283

Case III) Disjunctive Task Type

In this case is addressed the problem of team sizing considering a production system composed of multiple disjunctive tasks, when considering homogeneous team sizes and a heterogeneous workforce comprising 6 workers. As previously defined the team performance for disjunctive tasks is determined by the most competent member within the team (Steiner 1972), wherein in this work, team performance has been defined as the worker with the higher production output through a time horizon of 50-time periods.

System output has been defined as the summation of teams' outputs, considering that tasks between teams are independent. Each task in the production system is assigned to one only team and vice versa.

Using equation 4.40 the different team sizes (m=1,2,3,6) have been evaluated to determine the optimality conditions respecting δ for the described example. For a team size of one worker per team equation 4.40 simplify as

$$-7.1 < \delta \tag{4.64}$$

The level of δ is defined in a range of [0,1]. Therefore, equation 4.64 can be updated as

$$0 < \delta \tag{4.65}$$

From the result obtained for this case we can be concluded that a team size of 1 worker per team is the optimal team size consistently across all possible levels of degree of process loss, considering the defined range for possible values of δ and considering homogeneous team sizes, a heterogeneous workforce comprising 6 workers, and a percentage of knowledge transfer between workers of 50% (θ=0.5). The results have been validated simulating different instances of process loss (δ) on MATLAB. The results of the simulation are presented in Table 4.8. Given that a team size of one worker per team have been found as the optimal team size across all possible scenarios of process loss (δ), then is no needed further exploration of others team sizes.

Table 4.8 Results obtained from the simulation for different instances of δ for the production system composed of disjunctive tasks – Heterogeneous Workforce.

TS (workers/ team)	System Output (δ=0.15)	System Output (δ=0.20)	System Output (δ=0.25)	System Output (δ=0.35)	System Output (δ=0.5)	System Output (δ=0.75)
1	**5924****	**5924****	**5924****	**5924****	**5924****	**5924****
2	4769	4749	4730	4692	4634	4537
3	3314	3285	3256	3198	3111	2967
6	1673	1634	1594	1516	1397	1200

4.4 Conclusions

The present study explores the team formation problem in an organizational context, considering the simultaneous effect of experiential learning, knowledge transfer, and process loss on individual performance. A closed mathematical expression is presented in this work to determine the optimal team size when considering a team-based work setting and the effect of experiential learning, knowledge transfer, and process loss on the individual performance, wherein the individual performance has been defined as worker's productivity. This study specifically presents a mathematical expression to determine the optimal team size for a multiple-team environment without the need to solve the MINLP, for scenarios of homogeneous and heterogeneous workforce when considering homogeneous team size.

Specifically, the mathematical expressions provided in this work address the determination of optimal team sizes when considering that an equal number of workers is assigned to every team created in the system. The scenario of homogeneous workforce assumes that all workers have identical learning parameters, resulting in all workers within the workforce having equal productivity rates across the time horizon of interest. The scenario of heterogeneous workforce, at the other extreme, considers workers to have different learning parameters, resulting in all workers within the workforce having different productivity rates. Three system types are evaluated in this work: Case I) a production system composed of multiple additive tasks, Case II) a production system composed of multiple conjunctive tasks, and Case III) a production system composed of multiple disjunctive tasks. The main contributions of this study are:

- This study specifically presents a mathematical expression to determine the optimal team size for a multiple-team environment without the need to solve the MINLP. The study provides a closed mathematical expression that allows users to determine the optimal team size without coding or solving an MINLP. Therefore, this expression helps managers to address team sizing decisions in organizations, considering the effect of learning and team dynamics on worker productivity, without investing in specialized software or coding skills for solving the complete MINLP.

- The mathematical expression presented in this work reduces the computational capacity required to address the team sizing problem. Solving MINLP problems has been limited in the past by the instance size and constraints, given limitations in computational capacity. Specifically, this limitation is magnified when addressing combinatorics formulations. Previous works have been developed in the past to simplify MINLP formulations. However, to our current knowledge, the methods available require at minimum coding and solving at least an MINLP. The presented expression allows users to solve the team sizing problem when considering individual productivity as a function of individual learning and team dynamic, without coding or solving the MINLP. Similarly, the results obtained from this expression can be further used as an intermediate step to simplify the formulation of other problems of interest related to workforce management applications, such as the worker assignment problem or worker scheduling problem (Appendix B), when considering an organizational context with a teamwork-based policy. The a priori determination of team size as an intermediate step for the worker assignment problem or worker scheduling problem will help to reduce the complexity associated with the formulation of these problems and, in some cases, may enable users to solve larger instances of the problem.

- The present study addresses the team sizing problem in the context of multiple teams, when considering the joint effect of experiential learning, knowledge transfer, and process loss on individual performance. In general, the multiple-team formation problem has not been previously studied considering the effect of process loss and knowledge transfer simultaneously on system performance. Previous research has concentrated on exploring factors that affect team performance and that must be considered in the formation of teams. Studies that discuss the effects of knowledge transfer and process loss on team performance have generally considered these two factors separately.

Thus, the current study contributes to this gap on literature. This study facilitates managerial-level decisions on team formation at the enterprise scale, considering the joint effect of experiential learning, knowledge transfer, and process loss on individual performance and consequently on system performance. The consideration of these two factors simultaneously as part of the individual performance provides a more realistic view of the effect of team dynamics on team performance, wherein gains are obtained from having larger teams, translating to more human resources to complete a task, but at the same time losses are incurred as a consequences of coordination, motivation, and cooperation issues between workers within larger teams.

This study is limited to scenarios of multiple teams when considering homogeneous team sizes, meaning that every team created in the system has the same number of workers assigned to perform the task. The extension of the theorem to scenarios of heterogeneous team sizes is a topic of interest for future research. Similarly, this study addresses the team formation process in systems composed of multiple additive, conjunctive, or disjunctive tasks. The production systems evaluated in this work are defined as homogeneous with respect to task type. This means that only pure production systems are examined in this work, whereas hybrid production systems composed of combinations of task types are outside of the boundary of this study. Similarly, the proposed model to estimate the individual productivity represents a hypothetical case of team context, assuming that in these scenarios, individual worker performance is directly proportional to the effect of process loss. The proposed model is based on a broad range of individual behaviors, whereas in future work, this may be based on empirical distributions of these behaviors. The development of mathematical models, derived from experimental data, that relate the effect of knowledge transfer and process loss to individual worker performance in teamwork contexts remains a gap in the teamwork literature and will be an area of interest for future research.

Appendix 4-A. System Output for Production Systems for Case I. Additive Tasks, Case II. Conjunctive Tasks, and Case III. Disjunctive Tasks.

Homogeneous Team Size – Homogeneous Workforce

For systems composed of additive, conjunctive or disjunctive tasks when considering a production system composed of a homogeneous workforce and homogeneous team size system output is defined in a general form as

$$S_m = Nk(1 - \delta L_m)\left(\frac{r}{1+\theta(m-1)} e^{-\left(\frac{x+\,\theta x(m-1)+p}{r}\right)} + x\right)\Bigg|_{a}^{b} \qquad \text{(A-1)}$$

Wherein the for the case of additive tasks the parameter *N* is defined as the number of workers *W* that composed the workforce, and for conjunctive and disjunctive tasks the parameter *N* is defined as the number of teams (*W/m)* in the system.

The function of system output (A-1) can be defined as the combination of two mathematical functions (equation A-2), $K(m)$ and $G(m)$, wherein $K(m)$ and $G(m)$ has been expressed as K_m and G_m for simplifying the notation in subsequent expressions.

$$S_m = K_m G_m \tag{A-2}$$

The primary function K_m is defined as

$$K_m = Nk(1 - L_m\delta) \tag{A-3}$$

and the secondary function G_m is defined as

$$G_m = \frac{r}{1+\theta(m-1)} e^{-\left(\frac{x+\theta x(m-1)+p}{r}\right)} + x \Big|_a^b \tag{A-4}$$

As previously defined in the text, the parameter L_m from equation A-3 has been estimated through the regression model $L_m = -0.1 + 0.09m$, which was fitted with data presented in Peltokorpi and Niemi (2018). Parameters θ, and δ are bounded by 0 and 1, while parameters k, p, r takes values defined as real positive values greater than zero. Equation A-3 can now be rewritten as

$$K_m = Nk(1 + 0.1\delta - 0.09m\delta) \tag{A-5}$$

The function K_m as defined in equation A-3 is a regression model of decreasing value. K_m accounts for the productivity losses of the workers in the total output. The productivity loss in workers results from the effect of team dynamics on the individual productivity as consequence of coordination, communication and motivational issues that arise in team-based settings. Thus, as the value of the variable team size m increases, considering a fixed value of degree of process loss δ, the value of the function K_m decreases (Figure A-1).

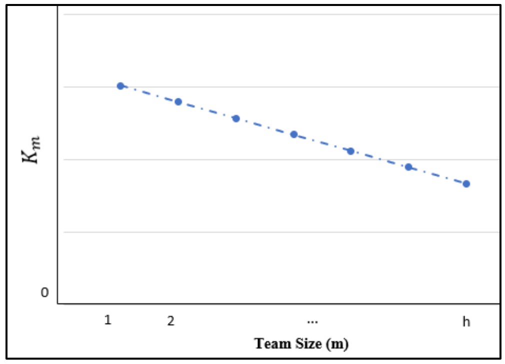

Figure A-1. Relationship of function K_m with variable m.

The function G_m as defined in equation A-4 is a non-decreasing monotonically expression for the specific domain of the considered parameters. Function G_m is composed of two components, wherein the first component (C_1) can be defined as the multiplication of the factors $\frac{r}{1+\theta(m-1)}$ and $e^{-\left(\frac{x+\theta x(m-1)+p}{r}\right)}\Big|_a^b$ and the second component (C_2) defined as the sum of the parameter x evaluated in the limits of b and a, that is $+\,x\,\Big|_a^b$. The factor E_1, $\left(\frac{r}{1+\theta(m-1)}\right)$, which corresponds to the first component of function G_m, has an inverse proportional tendency with respect to variable m, wherein θ and r are fixed parameters in the function with values as previously defined ($0 \leq \theta \geq 1$, $r > 0$). As the value of the variable m increases, the value of factor E_1, will have an asymptotic tendency to zero as shown in Figure A-2.

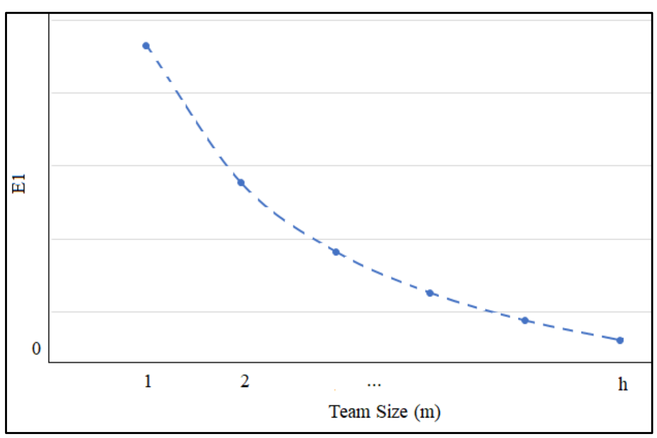

Figure A-2. Decreasing asymptotic tendency to zero that defined E_1 and E_2.

Factor E_2, $e^{-\left(\frac{x+\theta x(m-1)+p}{r}\right)}\Big|_a^b$, corresponds to the first component of function G_m, an exponential expression. Therefore, factor E_2 has a decreasing asymptotic tendency to zero, as variable m increases, wherein θ, r and p are fixed parameters in the function with values as previously defined ($0 \leq \theta \geq 1$, r & $p > 0$). As the value of the variable m increases, the value of E_2, will have an asymptotic tendency to zero as shown in Figure A-2. Thus, the expression presented as the component C_1 of the function G_m, results from the product of E_1 and E_2, and returns a smaller number as the value of the variable m increase. Specifically, the expression presented as the component C_1 is defined by a decreasing asymptotic tendency to zero.

The second component (C_2) of function G_m, is defined as the sum of the parameter x evaluated in the limits of b and a, that is $x\big|_a^b$. That means that the component C_2 returns a constant value. Therefore, when component C_2 is added to component C_1 as presented in function G_m, the result in the behavior of function G_m would be an increasing behavior which tends asymptotically to $b - a$. The function G_m then is defined as a non-decreasing monotonically function that asymptotically tends to $b - a$, as presented in Figure A-3.

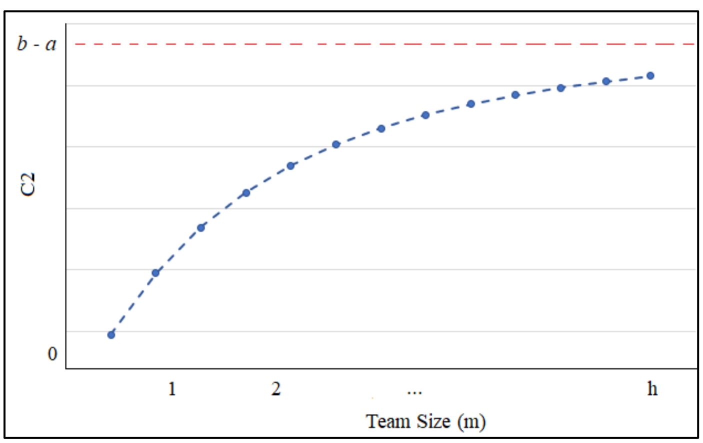

Figure A-3. Behavior of the function G_m.

While function S_m is a composition of the product of functions K_m and G_m, it is concluded that function S_m contains no more than one maximum point, considering a fixed domain of $m \in (1, h)$, fixed values of parameters W, k, p, $r > 0$, a fixed time horizon ($a \le x \le b$), and fixed values of parameters θ, δ ($0 \le \theta \le 1$, $0 \le \delta \le 1$). Thus, four possible function shapes can be obtained for the variety of the function instances within the specifications described above (Figure A-4).

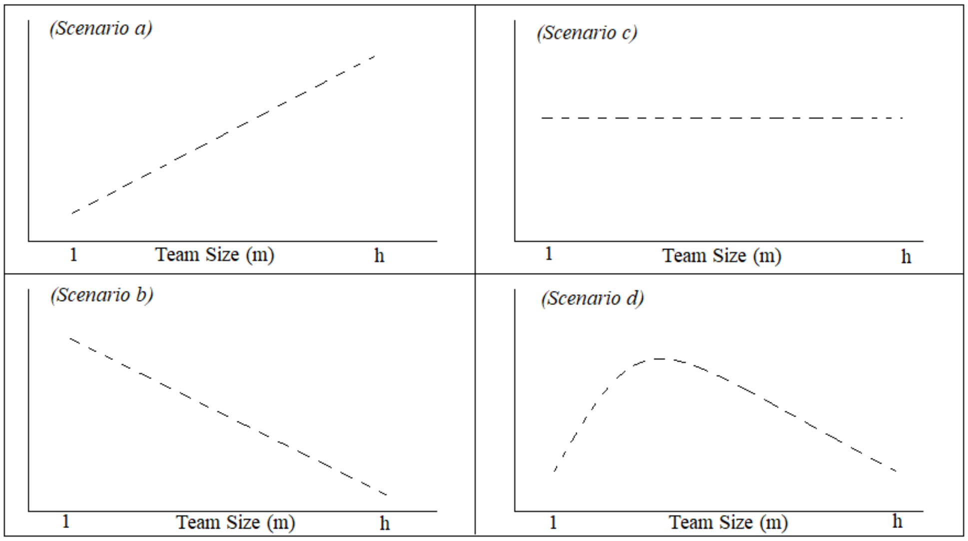

Figure A-4. Scenarios for the expression of system output.

The expression of system output S_m can take the form of a linear increasing function (Figure A-4. *Scenario a*), considering the fixed values of the parameters k, p, r, $W > 0$, a fixed value of parameter θ in the domain $0 < \theta \le 1$, a fixed value of parameter δ in the domain $0 \le \delta \le 1$, and a fixed time horizon ($a \le x \le b$). This scenario represents the case where the gaining of productivity associated with learning by knowledge transfer between workers overpass the losses associated with coordination, motivation and communication issues that arise as part of team dynamic. Therefore, the maximum value of system output S_m is associated with the lower bound of the variable team size m, considering m as a positive integer value.

Another possible scenario would be the expression of system output S_m taking the form of a linear decreasing function (Figure A-4. *Scenario b*). This scenario would be possible considering fixed values of the parameters k, p, r, $W > 0$, a fixed value of parameter θ in the domain $0 \le \theta \le 1$, a fixed value of parameter δ in the domain $0 < \delta \le 1$, and a fixed time horizon ($a \le x \le b$). This scenario describes the case where the gaining of productivity associated with learning by knowledge transfer between workers in a team-based work setting does not equal or overpass the losses associated with coordination, motivation and communication issues that arise as part of team dynamic. That means the sum of individual productivity losses associated with issues that arise as part of team dynamic are greater than the collaborative gaining associated with the effect of knowledge transfer between workers in the individual productivity. For this case, the maximum value of system output S_m is associated with the upper bound of the variable team size *m,* considering *m* as a positive integer value.

A third possible scenario for the function shape of the expression of system output S_m would be when the expression S_m takes the form of a linear horizontal function (Figure A-4. *Scenario c*) meaning that it neither increases nor decreases. This scenario occurs always that the values of parameter θ and δ are equal to zero (θ and δ = 0), considering fixed values of the parameters $k, p, r, W > 0$, and a fixed time horizon ($a \leq x \leq b$). This scenario is result of having a system where no benefits or losses are incurred from the effect of team dynamic. Therefore, if no benefits or losses in individual productivity are incurred as result of team size *m*, there is no difference in system output between dividing the workforce *W* in teams of size *m*-1, *m* or *m*+1, or any other feasible combination of *m*. That means, when is no individual productivity losses associated with issues that arise as part of team dynamic for all workers in the workforce *W*, and when workers cannot benefit from the effect of knowledge transfer between workers to improve their individual productivity, then there is no increase or decreases in the system output S_m as team size *m* change. Therefore, system output S_m no longer depends of team size *m*. For this case, there is no maximum or minimum value of system output S_m associated with the variable team size *m*. This scenario applies only for production systems defined by an additive task type.

Finally, the forth scenario that can be obtained for the expression of system output S_m when considering a production system defined by additive, conjunctive or disjunctive tasks, would be when the expression S_m initially increases until reach a maximum value of system output in m^* and decreases after this point, for values of $m > m^*$ (Figure A-4. *Scenario d*). This scenario would be possible considering fixed values of the parameters $k, p, r, W > 0$, a fixed value of parameter θ in the domain 0 <

$\theta \leq 1$, a fixed value of parameter δ in the domain $0 < \delta \leq 1$, and a fixed time horizon ($a \leq x \leq b$). This scenario represents the case where the gaining of productivity associated with learning by knowledge transfer between workers in a team-based work setting overpass the losses associated with coordination, motivation and communication issues that arise as part of team dynamic for values of team size $m < m^*$. Then, after a maximum value of system output is reached in a value of team size m^*, the system output will start to decrease as team size m increases over m^* as consequence of the sum of individual productivity losses associated with issues that arise as part of team dynamic are greater than the collaborative gaining associated with the effect of knowledge transfer between workers in the individual productivity. For this case, the maximum value of system output S_m is associated with a value m^* of the variable team size m, which is found within the range of values of the considered team size m but not in the upper or lower values of the variable domain of m.

All scenarios (Figure A-4) that can be obtained for the specified domain of the decision variable and function parameters ($k, p, r, W, m, x > 0; 0 \leq \delta, \theta \leq 1$) meet the conditions for concavity of the function. A function $f(x)$ is define as a concave if the $-f(x)$ is convex (Berkovitz 2002). A function $f(x)$ is convex if:

$$f(\lambda x_1 + (1-\lambda)x_2) \leq \lambda f(x_1) + (1-\lambda) f(x_2) \quad \forall\, x_1, x_2 \in S \qquad \text{(A-6)}$$

Thus, a function $f(x)$ is concave if the line segment joining any two points, $(x_{1,} f(x_1))$ and $(x_{2,} f(x_2))$, pertaining to graph of $f(x)$ lies entirely below or on the graph of the function $f(x)$. We can conclude that equation A-1, which represents the system output for the scenario of a production system composed of additive, conjunctive or disjunctive tasks considering homogeneous team sizes and homogeneous workforce, has no more than one maximum point. Thus, when a maximum point is found in equation A-1, this maximum point represents a global maximum.

Homogeneous Team Size – Heterogeneous Workforce

For production systems composed of additive, conjunctive or disjunctive tasks considering a heterogeneous workforce and homogeneous team size, the system output is defined in a general form as:

$$S_m = (1 - \delta L_m) \sum_{i=1}^{n} k_i \left(\frac{r_i}{1+\theta(m-1)} e^{-\left(\frac{x+\,\theta x(m-1)\,+\,p_i}{r_i}\right)} + x \right) \Bigg|_{a}^{b} \qquad \text{(A-7)}$$

$$S_m = (1 - \delta L_m)[Z_{1,m} + \sum_{c=1}^{\frac{W}{m}} k_{c+m} \left(\frac{r_{c+m}}{1+\theta(m-1)} e^{-\left(\frac{x+\,\theta x(m-1)\,+p_{c+m}}{r_{c+m}}\right)} + x \right) \Bigg|_{a}^{b}] \qquad \text{(A-8)}$$

$$S_m = (1 - \delta L_m) \sum_{j=1}^{\frac{W}{m}} k_j \left(\frac{r_j}{1+\theta(m-1)} e^{-\left(\frac{x+\,\theta x(m-1)\,+p_j}{r_j}\right)} + x \right) \Bigg|_{a}^{b} \qquad \text{(A-9)}$$

As for the scenario of homogeneous workforce, the function of system output for systems composed of additive (A-7), conjunctive (A-8) or disjunctive tasks (A-9) can be defined as the combination of two mathematical functions (equation A-10), $K(m)$ and $G(m)$, wherein $K(m)$ and $G(m)$ has been expressed as K_m and G_m for simplifying the notation in subsequent expressions.

$$S_m = K_m G_m \qquad \text{(A-10)}$$

The primary function K_m is defined as:

$$K_m = (1 - L_m \delta) \qquad \text{(A-11)}$$

and the secondary function G_m is defined as equation A-12 for the production system composed of additive tasks, equation A-13 for the production system composed of conjunctive tasks, or equation A-14 for the production system composed of disjunctive tasks.

$$G_m = \sum_{i=1}^{n} k_i \left(\frac{r_i}{1+\theta(m-1)} e^{-\left(\frac{x+\,\theta x(m-1)\,+\,p_i}{r_i}\right)} + x \right) \Bigg|_{a}^{b} \qquad \text{(A-12)}$$

$$G_m = k_1 \left(\frac{r_1}{1+\theta(m-1)} e^{-\left(\frac{x+\,\theta x(m-1)\,+p_{1+m}}{r_1}\right)} + x \right) + \sum_{c=1}^{\frac{W}{m}} k_{c+m} \left(\frac{r_{c+m}}{1+\theta(m-1)} e^{-\left(\frac{x+\,\theta x(m-1)\,+p_{c+m}}{r_{c+m}}\right)} + x \right) \Bigg|_{a}^{b} \qquad \text{(A-13)}$$

$$G_m = \sum_{j=1}^{\frac{W}{m}} k_j \left(\frac{r_j}{1+\theta(m-1)} e^{-\left(\frac{x+\theta x(m-1)+p_j}{r_j}\right)} + x \right) \Bigg|_a^b \tag{A-14}$$

As previously defined in the text, the parameter L_m from equation A-11 has been estimated through the regression model $L_m = -0.1 + 0.09m$. Parameters θ, and δ are bounded by 0 and 1, while parameters k, p, r, W takes constant values defined as real positive values greater than zero. Therefore, the properties of function K_m defined for the homogeneous workforce case (equation A-3) hold for the case of heterogeneous workforce (equation A-11), wherein function K_m for both cases, homogeneous and heterogeneous workforce, is defined by the general form presented in figure A-1.

As defined in equation A-4 for the case of homogeneous workforce, in general function G_m for the case of heterogeneous workforce, comprising the function G_m for the case of additive tasks (equation A-12), function G_m for the case of conjunctive tasks (equation A-13), or function G_m for the case of disjunctive tasks (equation A-14), is a non-decreasing monotonically expression for the specific domain of the considered parameters, $1 \leq \theta, \delta \leq 1$ and $k_i, p_i, r_i, W > 0$. These parameters are fixed for workers that composed the workforce W. That means as changing the team size m, these parameters θ, δ, k_i, p_i, r_i, W does not change. Therefore, in the three instances of function G_m for the case of heterogeneous workforce, G_m is composed of the summation of two components, wherein in general the first component (C_1) can be defined as the multiplication of the factors $\frac{r_i}{1+\theta(m-1)}$ and $e^{-\left(\frac{x+\theta x(m-1)+p_i}{r_i}\right)}\Big|_a^b$, and the second component (C_2) defined as the sum of the parameter x evaluated in the limits of b and a, that is $+\, x\,\big|_a^b$, wherein the incorporation of variability in the parameters of the function, that means every worker in the workforce having a different value of k_i, p_i, r_i, does not change the properties of the function G_m. Therefore, the values of function G_m would be defined increasingly asymptotically tending to $W(b - a)$ for the case of additive tasks *and* $\frac{W}{m}(b-a)$ for the case of conjunctive or disjunctive tasks. The function G_m then is defined as a non-decreasing monotonically function that asymptotically tends to $W\,(b - a)$ or $\frac{W}{m}(b - a)$, as presented in Figure A-3. Thus, the properties of function G_m for the case of homogeneous workforce hold for the case of heterogeneous workforce.

While function S_m is a composition of the product of functions K_m and G_m, it is concluded that function S_m contains no more than one maximum point, as described in the case of homogeneous workforce, considering a fixed domain of $m \in (1, h)$, parameters $W, k_i, p_i, r_i > 0$, fixed time horizon ($a \leq x \leq b$), and fixed values of parameters θ, δ ($0 \leq \theta \leq 1$, $0 \leq \delta \leq 1$).

Appendix 4-B. Illustrative Example: Worker Assignment Problem for Case I. Additive Tasks, Case II. Conjunctive Tasks, and Case III. Disjunctive Tasks.

A math programming formulation is defined below for the Worker Assignment Problem (WAP). The formulation considers workforce heterogeneity based on individual learning characteristics, and the effect of team dynamic on individual performance based on knowledge transfer and process loss. The WAP formulation presented below intends to determine the optimal team size for the multiple-team formation problem considering the maximization of system output for a specific time horizon as the objective function. The individual productivity is estimated using a modification of the 3-parameter exponential learning curve (Anzanello and Fogliatto, 2011), which intends to incorporate the effect of team dynamics on individual productivity through the concepts of knowledge transfer and process loss.

Assumptions:

The mathematical programming in this work was developed based on the following assumptions:

- There are n workers available to perform the tasks.
- The examined cases consider pure production systems which for Case I examine a system composed of additive tasks, Case II examine a system compose of conjunctive tasks, and Case III examine a system compose of disjunctive tasks. The model does not consider hybrid scenarios of these cases.
- The production system is divisible and its process is flexible. That means that the number of tasks of the production system is going to be determined by the number of teams created as part of the team formation process, where each task in the production system is assigned to only one team and vice versa.
- The system productivity is defined by the *sum of teams' productivity*, where the team productivity is determined by the task type of the production system. That means that the production system considered in this work assumed that tasks assigned between teams in the system are independent.
- A fixed time horizon of v = 50 time periods is considered in the model. The time horizon was selected considering a length of enough time to capture the learning process of workers, but not too extended in which the learning process effect get lost for the steady state behavior in the long run.
- The rate of learning is a function of how much time the worker has spent performing a particular task in a team with m-1 teammates and the percentage of knowledge that can be transferred (θ) from teammates.
- The process loss is a function of the team size m and the percentage of productivity that is lost (δ) given coordination, motivational and relational issues that workers face within the team.

- Workers are heterogeneous with respect to the worker's previous experience *p*, the steady state level *k* that will be achieved when the worker completes the learning process, and the cumulative production required to achieve a *k*/2 level of performance, represented by the parameter *r*.

Model Formulation

In this section a formal description of the model is presented for the three examined cases, additive, conjunctive and disjunctive, following the definition of the notation.

Sets:	
I	Set of workers $i = 1, 2, \ldots n$.
T	Set of time periods $t = 1, \ldots, v$.
M	Set of team sizes $m = 1,2, \ldots h$.
S	Set of teams in the system $s = 1,2, \ldots l$.

Parameters:	
p_i	Previous experience of worker i in the specific task.
k_i	Steady state level of productivity rate that worker i will achieve when the learning process be completed.
r_i	Cumulative production required by worker i to achieve a k/2 level of performance.
L_m	Maximum productivity loss that a worker can face when is assigned to a team of size m.
θ	Percentage of knowledge transferred from other workers performing similar tasks.

δ	*P*ercentage of individual productivity that is lost from the need for required coordination, the need to build relationships and communication links with other teammates, and the loss of motivation that results from working in a team context.
B	Number of workers.
A_m	Number of workers assigned to every team for a team size *m*.

Variables:	
$O_{i,m}$	Output from worker *i* assigned to a team of size *m* for the time horizon.
$Q_{i,m}^t$	Productivity if worker *i* is assigned to a team of size *m* during time period *t*.
$Y_{i,m}^t$	Binary variable indicating whether worker *i* is assigned to a team of size *m* during time period *t*.
$R_{i,m}$	Accumulated experience in time units by other workers different of worker *i* assigned to a team of size *m*.
X_m	Binary decision variable indicating whether a team size *m* is considered.
N	Number of teams composed when workers are grouped in teams of size *m*.
M_s	Binary variable indicating whether team *s* is created in the system.

Case I) Additive Task Type

The worker assignment problem for multiple-teams is addressed by the formulation presented below. The production system evaluated in this work consist of *N* additive tasks, where each task is assigned to a team composed of *m* workers through a time horizon of 50-time periods. An additive task has been defined as a task where the individual contributions of the team members are combined as a single output. Thus, the team performance is determined by the sum of the individual contributions of all team members (Steiner 1972). In this work, team performance has been defined as the team total output through a time horizon of 50-time periods. System output has been defined in this work as the summation of teams' outputs, considering that tasks between teams are independent, wherein the formulation considers teams of equal team size, that means al workers must have the same number of workers to perform the task.

This assumption has been made across all examined cases in this chapter and have been reinforced in the constraints of the problem formulation ***P*** presented below.

*Problem **P**: Worker Assignment Problem (WAP) for Case I) additive tasks*

$$Maximize \sum_{i=1}^{n}\sum_{m=1}^{h}\sum_{s=1}^{l} O_{i,m,s} \qquad (B-1)$$

$$O_{i,m,s} = \sum_{t=1}^{v} Y_{i,m,s}\, Q_{i,m}^{t} \qquad \forall\, i, \forall m, \forall s \qquad (B-2)$$

$$Q_{i,m}^{t} = k_i(1-\delta L_m)\left(1-e^{-\frac{tY_{i,m,s}+p_i+\theta R_{i,m}^{t}}{r_i}}\right) \forall\, i, \forall m, \forall t, \forall s \qquad (B-3)$$

$$R_{i,m}^{t} = (A_m - 1)tY_{i,m,s} \qquad \forall\, i, \forall m, \forall t, \forall s \qquad (B-4)$$

$$\sum_{m=1}^{h}\sum_{s=1}^{l} Y_{i,m,s} = 1 \qquad \forall\, i \qquad (B-5)$$

$$\sum_{i=1}^{n}\sum_{s=1}^{l} Y_{i,m,s} = X_m B \qquad \forall\, m \qquad (B-6)$$

$$\sum_{m=1}^{h} X_m = 1 \qquad (B-7)$$

$$N = \frac{B}{A_m} \qquad (B-8)$$

$$\sum_{i=1}^{n}\sum_{m=1}^{h} Y_{i,m,s} = A_m M_s \qquad \forall s \qquad (B-9)$$

$$\sum_{s=1}^{l} M_s \geq 1 \qquad (B-10)$$

$$\sum_{s=1}^{l} M_s \leq G \qquad (B-11)$$

$$X_m \in \{1,0\} \quad \forall\, m \quad (B-12)$$

$$Y_{i,m,s} \in \{1,0\} \quad \forall\, m, \forall\, i \quad (B-13)$$

$$R_{i,m}^{t} \in Z^{+} \quad \forall\, m, \forall\, t, \forall\, i \quad (B-14)$$

$$N \in Z^{+} \quad (B-15)$$

$$M_s \in \{1,0\} \quad \forall\, s \quad (B-16)$$

The presented formulation is proposed to determine the optimal team size of a production systems composed of multiple additive tasks. Equation B-1 represents the objective function of the model which is defined as the maximization of system output. As previously defined the system output is defined as the sum of teams' output, wherein specifically for the case of additive tasks team output is defined as the sum of the total productivity for a considered time horizon of individual workers within the team. Equation B-2 approximates the total output of worker *i* assigned to a team *s* of size *m* for the considered time horizon. Equation B-3 is used to estimate the productivity rate of worker *i* assigned to a team *s* of size *m* during time period *t*. In this work a modification of the 3-parameter exponential learning curve model is used to estimate individual worker productivity considering the effect of team dynamic in terms of knowledge transfer and process loss.

Equation B-4 quantifies the knowledge that can be transferred to a worker *i* from other workers assigned to the same team of size *m*. This equation captures the effect of knowledge transfer in the individual worker productivity rate considering workers experience in time units. For example, for a team of size *m*, while working together in a team during *t* time periods, a worker *i* can use $\theta t(m\text{-}1)$ units of experience of other colleagues assigned to the same team for improving their individual productivity. The θ value represents the percentage of this knowledge accumulated by other workers in the team, different to worker *i*, that can be used for worker *i* to improve their individual productivity during time period *t*. The percentage of knowledge that can be transferred (θ) is incorporated in equation B-3.

Equation B-5 ensures that worker *i* be only assigned to only one team across all available teams (s=1…l) and all considered team sizes (m=1…h), while equations B-6, B-7 and B-12 forced a homogeneous team formation policy in the system. That means that all teams must have the same number of assigned workers. Equation B-8 calculate the number of teams that can be formed if the available workforce is grouped in teams of size *m*. The formulation forces this ratio calculated in equation B-8 to be an integer positive value through equation B-15. That means that the number of workers needs to be divisible for the team size. For example, for a workforce composed of 10 workers, forming teams of size 3, meaning assigning three workers in each team, is not feasible. The division of the workforce (B=4) by the team size (m=3) returns a value that is not an integer value, therefore teams of size 3 for a workforce composed of 10 workers is not a feasible solution. Consequently, this solution is eliminated by the formulation through equation B-15.

Equation B-9 relates to the grouping of workers. This equation specifies that each created team within the system should have equal number of assigned workers. Equation B-10 and B-11 specifies that at least one team needs to be created within the system which corresponds to the case where all workers that composed the workforce are assigned together in one team, and that no more than *G* teams can be created within the system which corresponds the case where each worker is assigned individually to a task.

Equations B-13 defines a binary domain for the variable associated with the worker-team assignment. If the worker *i* is assigned to a team *s* of size *m*, then the variable will take a value of 1, otherwise the variable will take a value equal to 0. Equation B-14 defines the domain of the variable associated with the accumulated experience of other team members different of worker *i* in a team of size *m*, while equation B-16 defines the domain of the represents when a team *s* is created in the system. These variables have been defined in the domain of positive integer values.

*Problem **P'**: Worker Assignment Problem (WAP) for Case I) additive tasks*

The MINLP presented in problem ***P*** represents a mathematical formulation for solving the worker assignment problem in a multiple-team setting composed of additive tasks. When solving the formulation ***P*** it returns the team size and team in which each worker needs to be assigned to improve system output.

Theorem 1 can be implemented in this problem in order to simplify the complexity associated with the original formulation of problem ***P***. Thus, applying theorem 1 to formulation ***P***, the resulting formulation which we are going to denominate as formulation ***P'*** is presented below:

$$Maximize \sum_{i=1}^{n}\sum_{s=1}^{l} O_{i,s} \qquad (B-17)$$

$$O_{i,m,s} = \sum_{t=1}^{v} Y_{i,s}\, Q_i^t \qquad \forall\, i, \forall s \qquad (B-18)$$

$$Q_i^t = k_i(1-\delta L)\left(1 - e^{-\frac{tY_{i,s}+p_i+\theta R_i^t}{r_i}}\right) \quad \forall\, i, \forall s, \forall t \qquad (B-19)$$

$$R_i^t = (A-1)tY_{i,s} \qquad \forall\, i, \forall t, \forall s \qquad (B-20)$$

$$\sum_{s=1}^{l} Y_{i,s} = 1 \qquad \forall\, i\ \in I \qquad (B-21)$$

$$\sum_{i=1}^{n} Y_{i,s} = AM_s \qquad \forall s \qquad (B-22)$$

$$\sum_{s=1}^{l} M_s \geq 1 \qquad (B-23)$$

$$\sum_{s=1}^{l} M_s \leq G \qquad (B-24)$$

$$Y_{i,s} \in \{1,0\} \quad \forall\, i, \forall\, s \quad (B-25)$$

$$R_i^t \in Z^+ \quad \forall\, t, \forall\, i \quad (B-26)$$

$$M_s \in \{1,0\} \quad \forall\, s \quad (B-27)$$

The application of theorem 1 can be used to reduce the dimension of the formulation of original problem ***P***, determining a priori the optimal team size, and then using this information as an input for solving the reformulated problem **P'.** The reformulated problem ***P'*** addresses the worker assignment problem for multiple team settings considering that the optimal team size is already known. Reducing the dimensionality of formulations in the past has been associated with reduction in computational complexity associated with solving the original MINLP problems and consequently in facilitating the solution of bigger instances of the problem (Nembhard and Bentefouet 2012).

Case II) Conjunctive Task Type

For this case the production system will consist of *N* conjunctive tasks. Each task in the system is assigned to a team composed of *m* workers through a time horizon of 50-time periods. Conjunctive tasks have been defined as a task in which every member in the team needs to develop a part of the task in order to achieve the task's completion. In this scenario, a main divisible task is divided in smaller elements, and every element of the task needs to be completed in order to finalize the task. The performance of the team for conjunctive tasks is determined by the least competent member of each team (Steiner 1972). In this work, team performance has been defined as the team total output through a time horizon of 50-time periods. Specifically, for a system composed of conjunctive tasks, this work defines team total output as the output of the less productive worker of each team for the considered time horizon. Therefore, system output is defined as the summation of teams' outputs, considering that tasks between teams are independent. This assumption has been made across all examined cases in this work.

The problem formulation for the case of conjunctive is the same than the formulation previously introduced for the case of additive tasks, substituting the objective function presented in equation B-1 for equation B-28 for the case of conjunctive tasks.

$$Maximize \sum_{s=1}^{l} \min_{m \epsilon M,\ i \epsilon I} \{O_{i,m,s}\} \qquad (B-28)$$

Equation B-28 represents the objective function of the model which is defined as the maximization of system output. The system output is defined in this work as the sum of teams' output, where for conjunctive tasks team output is defined as the productivity of the less productive member within the team for the specific time horizon.

*Problem **P'**: Worker Assignment Problem (WAP) for Case II) conjunctive tasks*

The application of theorem 1 can be extended to the case of a production system composed of multiple conjunctive tasks. Reformulation ***P'*** previously presented for the case of additive tasks holds for the case of conjunctive tasks, substituting equation B-17 for equation B-29.

$$Maximize \sum_{s=1}^{l} \min_{i \epsilon I} \{O_{i,s}\} \qquad (B-29)$$

Case III) Disjunctive Task Type

For this case the production system will consist of *N* disjunctive tasks. Each task in the system is assigned to a team composed of *m* workers through a time horizon of 50-time periods. Disjunctive tasks represent an indivisible task, wherein all workers need to work together simultaneously in a task in order to reach it completion. As defined by Steiner (1972) the performance of teams for disjunctive tasks is determined by the most competent member of each team. In this work, team performance has been defined as the team total output through a time horizon of 50-time periods. Then, for a system composed of disjunctive tasks, the team total output is defined as the output of the most productive worker within the team for the considered time horizon. Therefore, system output is defined as the summation of teams' outputs, considering that tasks between teams are independent. This assumption has been made across all examined cases in this work. The problem formulation for the case of disjunctive tasks is the same than the formulation previously introduced for the case of additive tasks, substituting the objective function presented in equation B-1 for equation B-30.

$$Maximize \sum_{s=1}^{z} \max_{m \epsilon M,\ i \epsilon I} \{O_{i,m,s}\} \qquad (B-30)$$

*Problem **P'**: Worker Assignment Problem (WAP) for Case III) disjunctive tasks*

Similar that for the case of conjunctive tasks, the application of theorem 1 can be extended to the case of a production system composed of multiple disjunctive tasks. Reformulation ***P'*** previously presented for the case of additive tasks holds for the case of conjunctive tasks, substituting equation B-17 for equation B-31.

$$Maximize \sum_{s=1}^{l} \min_{i \epsilon I} \{O_{i,s}\} \qquad (B-31)$$

As previously discussed, this is an illustrative example where theorem 1 can be implemented to reduce the dimensionality of original formulations related to the worker assignment problems in settings wherein is desired to considers a team-based assignment rule. The application of theorem 1 does not limits only to this problem or this formulation. It can be applied to other problems as for example the scheduling to reduce the dimensionality of the problem when considering a team-based assignment policy for the development of workforce management plans.

CHAPTER 5

Conclusions and Future Research

The presented work addressed the team formation problem considering a learning model as estimator of workers' productivity, wherein the learning model incorporates the effect of experiential learning, learning by knowledge transfer, and process loss on individual workers' productivity. The factors of knowledge transfer and process loss represented the effect of team dynamic on individual performance.

The implementation of teams as an approach for workforce management may benefit the organization's productivity by improving the learning process of workers for the assigned task through the effect of knowledge transfer. However, the implementation of teams may also bring negative aspects, including the effect of process loss on individual productivity. Studies have suggested the effect of process loss and knowledge transfer as a function of team size, wherein larger teams have more available human resources and available knowledge than smaller teams but are also correlated with productivity losses due to the additional effort required from individuals to coordinate and communicate with other team members to efficiently perform tasks. Therefore, the design of teamwork in organizations, such as the determination of optimal team size and grouping of workers, has become an increasingly relevant topic in the literature of workforce management.

The present study addressed the gap of exploring the team formation problem considering the effect of knowledge transfer and process loss on individual productivity and finally on system performance. Prior to this study, most of the existing literature related to teamwork focused on exploring the factors that cause process loss or knowledge transfer separately, but the joint impact of process loss and knowledge transfer on team performance and its effect on team formation remained unsettled. This work addressed this gap, focusing specifically on studying the joint impact of process loss and knowledge transfer on team performance and its effect on team formation, evaluating team formation mainly from the perspective of team sizing. The main findings of this work are presented below.

- This study addressed the team formation problem considering the effect of team dynamic on individual productivity and consequently on system performance. In general, three task types have been considered as part of the study: disjunctive, conjunctive, and additive, which are representative of tasks commonly found in production-based organizations.

- For conjunctive, disjunctive, and additive tasks, team dynamic showed a significant effect on system performance, where team dynamic is defined as a function of the team size and system performance is defined as total productivity over a fixed time horizon. Previous studies have shown the impact of team dynamics on system performance, considering team dynamics from the positive perspective of knowledge transfer or the negative perspective of process loss. The literature lacked studies that considered the effect of both knowledge transfer and process loss simultaneously on individual productivity and consequently on system performance, which would provide a more realistic picture of the effect of team dynamics on individual productivity. This study addressed this gap, further providing a hypothetical model that accounts for the gains and losses in individual productivity resulting from team dynamics.
- For the three task types, the findings of this study demonstrate that team size had a significant effect on team performance, highlighting the importance of its consideration as part of a teamwork strategy implementation. The application of a teamwork strategy was shown to be beneficial for team performance in some task scenarios, as compared to assigning workers individually to perform tasks, when considering the effect of team dynamic on individual productivity and system performance.
- Organizational factors such as workforce heterogeneity, tasks heterogeneity, and system dimensionality had a significant effect on system performance, differing with respect to the task type. These findings highlight the impact of considering organizational factors in addition to human factors in the design and implementation of a teamwork strategy in production-based organizations.
- A mathematical expression is presented to determine the optimal team size for a multiple-team environment—without the need to solve the MNLIP—for a production system composed of pure additive, conjunctive, or disjunctive tasks, when considering homogeneous team sizes. The proposed mathematical expression facilitates managerial-level decisions on team formation at the enterprise scale

when considering the effect of workforce heterogeneity, experiential learning, knowledge transfer, and process loss on system performance.

The dissertation concludes by pointing to potential directions for future research. The thesis focuses on the effect of team dynamics on individual performance and system performance, wherein team dynamics are modeled with the concepts of knowledge transfer and process loss. The effect of process loss and knowledge transfer have been studied in isolation in past works. Although the literature does explain how these factors affect individual performance and team performance, there is a lack of mathematical models to represent the joint effect of knowledge transfer and process loss on individual performance. The model used in this work represents a hypothetical case of team context, assuming that in these scenarios, individual worker performance is directly proportional to the effect of process loss. The development of mathematical models, derived from experimental data, that relate the effect of knowledge transfer and process loss to individual worker performance in teamwork contexts remains a gap in the teamwork literature and will be an area of interest for future research. Similarly, this research addresses static instances of production systems considering limited system structures, in most cases composed of only one type of task. The extension of the study of team formation to broader scenarios, such as hybrid production systems and systems represented by a dynamic behavior, would be an area of interest for future studies. The representation of production systems as dynamic organizations must provide a more realistic scenario of an organization and, consequently, more accurate managerial decisions with respect to workforce management.

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