JOSE ANTONIO LARCO MARTINELLI

# Incorporating Worker-Specific Factors in Operations Management Models

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Modellering van menselijke factoren in operations management

Thesis

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*To my family: Cecilia, José Antonio, Vanessa y Carlos*

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José Antonio Larco

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# Chapter 1

# Introduction

## 1.1 Motivation

Operations management is concerned with the production of goods and services in organizations. Behind every production activity workers are involved. Workers transform goods, handle goods, service clients, operate and maintain equipment. They perform all these activities so that in the end a good or a service can be offered to a customer. Without workers, offering such goods and services would be impossible. The involvement of workers in the production of goods and services forces a direct relationship between worker performance and system productivity.

At the same time, the workers' performance and satisfaction with their job can, in turn, be influenced by operations management decisions. How schedules are assigned to workers, which production goals are assigned to workers and where products are located in a warehouse are all examples of such decisions. Operations management decisions can make work more (or less) demanding, challenging, easier to execute, motivating, comfortable and fatiguing. By altering these attributes, both, individual performance and the workers' satisfaction are affected. The workers' job satisfaction is then ultimately linked to the workers' well-being. In a context where firms consider not only the maximization of shareholder value, but also the well-being of all their stakeholders (Dahlsrud, 2008), the well-being of workers should be included as an objective in the firm's operations.

Operations management decision models, using operations research techniques, seek maximal improvement of one or more operations management objectives through the definition of optimal levels of a number of decision variables. This thesis addresses how to enhance operations management decision models by considering the impact of these decisions on the workers' individual performance (and subsequent system performance) as well as the workers' satisfaction with the job. By so doing, this thesis also addresses the concern that human considerations should be examined to enrich the operations management field; a concern repeatedly raised in recent years by operations management scientists (see Boudreau et al. (2003), Bendoly et al. (2006) and Gino and Pisano (2008)). In sum, we agree with the recommendation for the field of operations management made by Powell and Johnson (1980):

"If the worker has one iota of discretion he must be considered a determinant of the productive outcome."

Despite remaining largely unaddressed throughout the history of the Operations Management field, this concern for human considerations is not new. Already, in 1914, L.M. Gilbreth made an attempt to include knowledge of psychology in the field of scientific management, which at that time was largely devoted to operations management issues. In particular, Gilbreth (1914) reported studies regarding work place variables like the measurement of work, balancing individual welfare and productivity as well as the use of incentives, among others. Similarly, Taylor (1911), also closely studied the behavior of workers in the workplace, even if his efforts were limited and made unrealistic *a priori* assumptions about the workers' behavior.

Even in the current state of the art of the operations management field, questions remain regarding the involvement of workers in operations. How to best design incentive schemes for boosting performance and how to balance individual welfare and system performance objectives in a production system, are just a few of the questions that remain unanswered. A better understanding of the mechanisms governing how workers perform their job and are affected by their productive context provides an untapped opportunity for better operations management design decisions. Better decisions may lead to not only more cost-effective, responsive and reliable productive systems, but also to productive systems that accommodate their workers better. A common thread throughout this work is to take a dual approach. First, gain understanding about the worker-productive system interaction; and second, use this understanding to inform operations management decision models.

## 1.2 Research Methodology

As the subject of this thesis is inherently multidisciplinary, this dissertation makes use of different bodies of knowledge in both research and methodology. In particular, this thesis makes use of knowledge from psychology, ergonomics and operations management. From psychology, the field that studies human mental functions and behavior, this thesis draws from relevant theories of motivation and factors that affect motivation, effort regulation and work evaluation. Next, from the field of ergonomics, a field concerned with the understanding of interactions among humans and other elements of a system (IEA, 2000), this thesis draws from results of physical and mental capabilities of humans. Lastly, from the field of operations management, this thesis draws upon existing knowledge regarding performance metrics and operations decisions, in particular, in the context of warehouse operations. It is in the context of warehouse operations that most of the studies in this dissertation are directly applied. This dissertation thus lies at the intersection of three fields and uses the knowledge in these fields to generate hypotheses regarding the impact of operations management variables on individual welfare and performance.

These hypotheses are then tested using empirical research methods. The value of empirical research methods for building and testing theory in operations management were highlighted by Roth (2007). This dissertation uses two empirical research methods. First, we make use of experimental methods to manipulate goal levels and study their effects in performance and work pace regulation. Experimental methods have recently been recognized as a new tool for furthering the knowledge of operations management by Croson and Donohue (2002). Second, we make use of a field study to identify and quantify the influence of location factors in the productivity and perceived discomfort of real workers. The hypothesized relationships are then tested on the collected data via a number of statistical procedures. Furthermore, because precise mathematical relationships are needed for operations management models, we make use of a family of linear regression methodologies to characterize, specify and formulate empirical models of the proposed relationships.

These empirical models are then used as an input for analytical operations decision models. In particular, based on empirical models of cycle time and discomfort in an order picking task, we formulate a bi-objective assignment model to decide on the locations of products within a warehouse in order to make order picking activities more efficient and worker-friendly. It is also worth noting here that we make use of analytical modeling in an unconventional manner: To derive hypotheses regarding how workers regulate their effort to achieve goals, we model the workers' choice of how much effort to exert over time to derive hypotheses regarding how workers regulate their effort to achieve goals.

## 1.3 Contribution and thesis outline

The main contribution of this thesis is to incorporate results of the behavior and ergonomic sciences in operations management decisions. To achieve this contribution, this thesis addresses two main challenges. First, the challenge of identifying results of behavior and ergonomic sciences and validate these for specific operations management contexts. Second, the challenge of describing the validated results in a mathematical format adequate for modeling decisions in operations management.

By addressing these challenges, we are able to develop new operations management models that take into account worker related factors that are relevant because they either affect the objective or the feasibility of the decision models. In a way, this dissertation can be seen as a response to the call for operations management models that incorporate insights from the behavioral and ergonomic sciences (Boudreau et al., 2003).

The studies within this dissertation all follow a common sequence. First, for theory building, hypotheses are generated based on existing bodies of knowledge and theoretical decision models. Second, for theory testing, the hypotheses are tested using either a field study or a laboratory experiment. Using regression techniques, empirical models of the effects of operational variables on performance and job satisfaction metrics are constructed and tested. Third, the results of these empirical models are used for gaining insights for operations management. These insights are either gained through a discussion of its application or by using the models to formulate analytical operations management decision models that are applicable for specific contexts. Figure 1.1 shows an overview of how this dissertation is organized by using this three step approach throughout its chapters. We detail the contribution of each chapter as follows.

**Behavioral operations for workers: Challenges and opportunities.**

Chapter 2 introduces modeling and empirical considerations for the inclusion of worker specific factors in operations management decision models. Centered on operations management decisions, our goal is to provide a review of relationships found in the literature that link worker specific factors, worker performance, and job satisfaction to operations management decision variables. We contribute to the interface of operations management and behavioral sciences by evaluating whether the relationships documented in the literature are undisputed and whether these are characterized in a way that allows for mathematical description. In addition, we propose frameworks integrating a number of worker related factors that can be influenced by operations management decisions and affect operations management objectives. Based on the evaluations and frameworks proposed, we provide recommendations explaining how to incorporate such relationships into current operations management models. Moreover, the chapter is also of interest for empirical scientists as we identify current limitations on the knowledge of human factors and its interactions that are critical for advancing current operations management decision models.

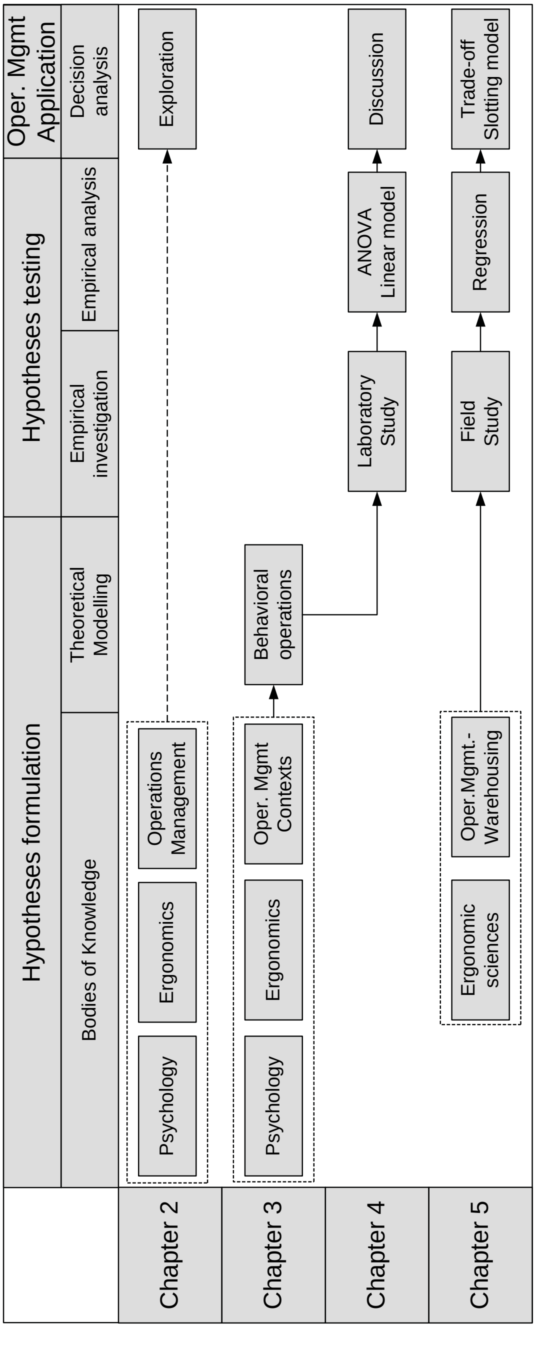



Figure 1.1: Structure of the dissertation

**How do workers regulate their effort when goals are assigned? A theoretical approach.**

Operations management models of work flow typically assume that workers are unaffected by external factors. This assumption is contradicted by a major theory within Organizational Behavior, referred as Goal Setting Theory. This theory posits that setting challenging goals enhances performance. In Chapter 3, we introduce the concept of setting goals for enhancing worker performance. We review the existing literature on how to set goals (i.e. goal setting) from the field of industrial psychology and identify two main questions that remain unanswered in operations management contexts. The first question is how workers perform given increasing levels of difficulty for the goals assigned to them. The second question is how workers regulate their work pace when a goal and a deadline are assigned to them. Two decision making models are proposed based on alternative views from behavioral economics; one that assumes myopic behavior of workers and another that assumes planning behavior. Thus, we obtain alternative propositions regarding the relationship between the goal difficulty and work pace regulation of workers. We then contribute by developing a theory of goal setting for operations management contexts where regulation of effort over time is the critical factor.

**How do workers regulate their effort when goals are assigned? An empirical inquiry.**

Chapter 4 continues the theoretical investigation of Chapter 3 by testing it empirically. As no theory is available for predicting *a priori* which behavior is dominant for workers (whether a worker exhibits myopic or planning behavior), we conduct a lab experiment in which we observe worker performance under a variety of conditions. Unlike previous experiments in goal setting theory, the experiment performed incorporates the assignment of goals and deadlines at the same time and tracks the evolution of the participants' work pace over time. From the experiment, we find general support for the planning model. We confirm a strictly increasing relationship between goal difficulty and performance as well as differences in goal sensitivity across individuals with different skill levels. More importantly, by investigating work pace regulation, we find previously unknown advantages of setting challenging goals. Specifically, we find that assigning challenging goals induce workers to work at a stationary work-pace and in more predictable patterns. We discuss possible explanations for these findings as well as their implications for operations management.

**Enhanced storage slotting decisions: considering the human element.**

Chapter 5 recognizes that there is a tendency in both, practice and academia, to emphasize operational performance in warehouse design decisions without considering the impact these decisions have on the workers' well-being. Humans, however, are often at the heart of crucial processes such as order picking. We contribute to the literature and practice of warehouse design by considering both, an economic and a well-being goal, in storage slotting decisions. The traditional economic goal is that of minimizing cycle time, whereas the human well-being goal is that of minimizing workers' discomfort. Our approach is data driven, since little of the needed information is readily available. We first build empirical models for estimating cycle times and discomfort in order picking operations. These empirical models are then used to formulate a bi-objective assignment model where products are assigned to specific locations. The results and subsequent analysis show moderate trade-offs and considerable alignment between both goals. We also provide practical recommendations based on these results for storage assignment decisions.

# Chapter 2

# Behavioral operations for workers: Challenges and opportunities

## 2.1 Introduction

Since the early days of the operations management field, the challenge of incorporating relevant aspects of worker behavior in Operations Management (OM) decision models has been persistent. Already in 1955, Hayes noted the difficulty of including the effect of decisions on the firms' personnel within mathematical models. More than fifty years later, Gino and Pisano (2008) observed that "the behavioral perspective has largely been absent in the field of operations" and, by extension, in models of operations management. The emerging research stream of Behavioral Operations attempts to address this challenge by studying the impact of operational decisions on people. However, this field also studies cognitive limitations and biases of decision makers in the operations function. In fact, more studies focus on the behavioral aspects of managers' and planners' decisions than that of workers. An emerging question is then, if the general call for incorporating behavioral insights into operations management decision models (e.g. see Bendoly et al., 2006 and Gino and Pisano, 2008) should also include a specific focus on the behavioral insights of workers.

We reason that the answer to this question is affirmative and that there are two worker-related cases for which incorporating such insights may be important. In the first case, performance of a productive system is affected indirectly by operational policies as a result of changes in the behavior and performance of individual workers. If, for example, a shift schedule is too demanding on the workers, it may generate fatigue and decrease individual motivation to perform, as well as the capacity to perform itself. Thus, a schedule that is too demanding will compromise the original objective of cost effectiveness. This example illustrates the approach taken in this thesis. Specifically, we take a general view of human behavior, including mental and physical aspects (such as fatigue) that drive individuals' actions.

In the second case, operational policies influence worker satisfaction with their jobs. Although the traditional objectives in operations management models (e.g. minimization of operational costs, response times, and quality errors) stem from the classic profit maximization directive of the firm (Friedman, 1962), we argue that objectives concerning the maximization of the workers' job satisfaction should also be included. Workers are important stakeholders in the firm: contributing with their work to the firms' profitability, spending a considerable amount of their time at the job and depending on their job for sustaining themselves and their families (Pfeffer, 2009). Hence, for firms that view their goal as not only creating value for their shareholders, but also satisfying all their stake-holders (Dahlsrud, 2008), it logically follows to incorporate worker satisfaction as an operational objective. In addition, including job satisfaction in a firm's objective also yields other benefits that make job satisfaction an even more desirable objective for a firm. These benefits include, among others, the improvement of worker performance, economic savings in lower accident and absenteeism (Daley et al., 2009) rates, as well as lower worker turnover (Porter and Steers, 1973).

In both cases, the failure to include ways by which operational decisions influence workers may result in operational decisions that are either sub-optimal, infeasible or simply not aligned with the objective of stakeholder satisfaction. In order to correct such flawed decisions, we call, in this chapter, for a worker specific focus of operations management decisions.

In this chapter, our goal is to review the existing knowledge that links operations management decisions with worker performance and worker job satisfaction. We, in turn, explore ways to incorporate these insights in existing and potential operations management decision models. Note that these operations management decision models are normative, in the sense that seek to optimize for an operationalized objective.

This chapter is relevant for both, operations management modelers and empirical researchers. For modelers dealing with operations involving workers in key roles, our review may enable them to obtain the required information to describe worker-related human factors relationships in a mathematical format for incorporation into decision making models. For empirical researchers that wish to contribute to operations management decision models, this chapter may guide their research efforts by detailing what knowledge is still unknown and is still required for effectively incorporating relevant worker-related human factors in operations management models.

This chapter contributes to the operations management field by integrating dispersed knowledge of worker related factors into a framework that can be used to incorporate these factors within operations decision models. Our framework is decision-making driven, focusing on the proven relationships, from literature, between operations decisions and worker-specific factors that may affect the optimality and feasibility of such decisions. In this way, we reduce the scope of the worker related factors to those that are directly relevant to operations management decisions. The advantage of a decision-making driven approach to review the existing knowledge, as compared to a theoretical based (see Boudreau et al., 2003, Gino and Pisano, 2008 as well as Bendoly et al., 2010), assumption based (Bendoly and Prietula, 2008) or case intervention based (Neumann and Dul, 2010) approach is that it enables a discussion centered on the adequacy and limitations of the mathematical description of such relationships. Based on the discussion of such limitations, we are able to provide recommendations for modelers seeking to incorporate current knowledge of worker specific factors. Similarly, we are also able to provide recommendations for empirical researchers to address the limitations of current knowledge that impede further incorporation of worker related factors into operations decision models. The combination of both, axiomatic decision modeling and empirical research has been singled as a fruitful approach to advance Operations Management theory (for a discussion see Bertrand and Fransoo (2002) and Roth (2007)).

To achieve our goal, we address four questions in this chapter: 1) What are the relationships that link operational decisions and individual work performance? 2) What are the limitations of the description of such relationships in terms of mathematical characterization? 3) What are the dimensions or facets of job satisfaction and which of them can be influenced by operations management variables? 4) What are common decision variables in operations management models that may influence either individual work performance or individual job satisfaction?

This paper is structured as follows. In Section 2.2 we propose a general framework for incorporating worker specific factors inoperations management models. In Section 2.3, we provide a detailed account of worker specific factors with individual performance and evaluate how to incorporate these in operations decision models. Similarly, in Section 2.4, we review existing literature on factors contributing to job satisfaction and evaluate which of these can be incorporated into operations management decision models. Section 2.5, illustrates how common decision variables in operations management models may affect the previously identified worker-related human factors. We conclude in Section 2.6 with a brief summary of our approach and main lessons learned. Throughout the sections, recommendations for furthering modeling and empirical based research are given.

## 2.2 Modeling framework

To incorporate worker-related human aspects into operations management decision models, we propose a general framework as depicted in Figure 2.1. The framework first identifies two levels of analysis, a productive system level, which could refer to any system that adds value (e.g. a production line, a packaging system, a call center), and an individual level which models the worker and his personal exposure to environmental conditions that the productive system defines. Most analytical models in operations management operate only at the productive system level by modeling how decision variables in operations directly impact operational performance (arrow 1 in Figure 2.1). We propose two alternative indirect paths for modeling in operational models. One concerns the path by which operations management variables affect individual performance and the other concerns the path by which operations management variables affect the job satisfaction of individuals in a productive system.

In the proposed framework, we refer to individual performance specifically for operational contexts. Hence, performance refers to classic objectives within the operations management function, including productivity, quality and the ability to meet deadlines. However, given that the majority of the literature addresses determinants of worker performance in terms of the specific dimension of productivity, in this chapter, we refer to productivity measured as tasks processed per unit of time, unless stated otherwise.

For the concept of job satisfaction, we use the definition of Weiss (2002) that defines job satisfaction as a "positive (or negative) evaluative judgment one makes about one's job or job situation". In this way, job satisfaction is defined as an attitude towards the job where an attitude is defined as a "summary evaluations of an object (e.g. oneself, other people, issues) along a dimension ranging from positive to negative" (Petty et al., 2002). We also acknowledge that other definitions of job satisfaction exist. For example, Smith et al. (1969), Locke (1976) and Cranny et al. (1992), propose that job satisfaction is an affective or emotional response to the job. However, we do not use any of these other definitions because these definitions differ with the way how job satisfaction is most commonly operationalized an measured. Most commonly, for measuring job satisfaction, respondents are asked to evaluate on a scale (negative to positive) one aspect of, or the totality of, the job (Weiss, 2002). Hence, the definition provided by Weiss (2002) is most consistent with how job satisfaction is measured in practice.

The path to influence individual performance and job satisfaction starts with a transformation of the operations management decision variables into individual exposure variables measuring the extent to which an individual is subject to given stimuli (e.g. hours of work, queue length, observed work pace of peers). To illustrate this, consider the case of constructing a shift schedule that minimizes staffing costs. Suppose workers may be assigned either to morning or night shifts and to shifts that are either 8 or 10 hours in duration. One decision variable may be the assignment of an individual from the pool of workers to a given shift (i.e. an individual employee-shift pair). Given this example, an exposure variable, that provides an indication of the extent to which a worker is exposed to a strainful shift may be the individual's average number of hours between two consecutive shifts.

The next step is then to link the exposure variable to individual performance and/or satisfaction of an individual with the job. Although this step can be done in a direct way, in the framework, intermediate variables are used so that these variables can be referenced and identified from the existing literature as reviewed in Sections 2.3 and 2.4. These variables are referred

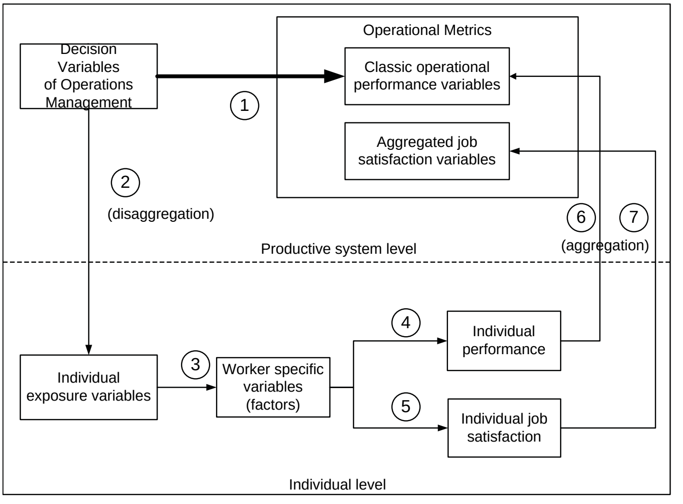



Figure 2.1: Framework for modeling worker-specific factors for operations management

to in the framework (Figure 2.1) as worker specific variables (or factors) and include variables internal to the worker such as fatigue, discomfort, the level of skill and cognitive demands that affect either individual performance or job satisfaction (depicted in Figure 2.1 by arrows 4 and 5). Continuing with the previous example, the exposure variable of average number of hours between schedules may then be related to an intermediate variable such as fatigue measured subjectively, through self-perception (Beurskens et al., 2003). Fatigue, in turn, may then be linked with a decrease in performance and possibly also with a decrease in job satisfaction if fatigue becomes chronic. In Section 2.3, we review existing relationships in the literature that link exposure variables with worker specific variables and individual performance (depicted in Figure 2.1 by arrows 3 and 4 respectively). Similarly, in Section 2.4, we review existing relationships in the literature that link exposure variables with worker specific variables and job satisfaction (depicted in Figure 2.1 by arrows 3 and 5 respectively). We also note that certain worker specific variables exist that contribute to both, a worker's individual performance as well as job satisfaction. These work specific variables contributing to both individual performance and job satisfaction, include fatigue, feedback provided, frequency of interaction with peers. It is these variables that generally affect the intrinsic desirability of the job.

It is also worth noting that an aggregation procedure is required to model the impact of individual performance (depicted in Figure 2.1 by arrow 6). This procedure depends largely on the objective of the operations management decision model. For example, if minimization of the makespan or tardiness is considered the main objective in a productive system, then the effect of increasing individual productivity on the desired objective may be non-trivial and may even be dependent on specific problem instances (i.e. release dates, duration of jobs and deadlines of jobs). By contrast, if, in a parallel productive system, the desired objective is a maximization of throughput then, the aggregation is straightforward.

Finally, in order to aggregate individual job satisfaction levels at the production level, a manager is forced to make a choice regarding the aggregation procedure (depicted in Figure 2.1 by arrow 7). For example, the decision maker should ask himself whether he should optimize for the average, the lower quartile, or the minimum job satisfaction related metric of the workers involved in the production system. The decision maker may, in fact, choose to design a productive system for a worst-case scenario in terms of job satisfaction. This procedure will be illustrated in Section 5 through the use of explicit examples.

However, as job satisfaction objectives can usually coexist with classical operations management model objectives, multi-objective optimization may be required (Ehrgott, 2000). In this case two types of analysis are possible: 1) A general trade-off analysis between satisfaction related objectives and performance. This allows one to establish the costs of additional operational performance in terms of an improved level of job satisfaction. 2) An analysis of all available non-dominated solutions.

## 2.3 Individual performance

To integrate the different mechanisms by which operations management decision variables may affect individual performance, we propose an integrated framework (Figure 2.1). The advantage of an integrated framework is that it allows one to account for the effects of multiple operational variables that may simultaneously affect more than one individual performance factor.

When modeling production decisions, the framework for modeling individual performance can be used in two ways. One way is by directly relating decision variables to individual performance and another way is by relating decision variables to individual performance through intermediate factors. The latter approach is more suitable when there is more than one operational variable and more than one individual performance factor at play.

Several human factors influence employees' productivity. One of the earliest models of employee productivity is that of Vroom (1964) where he proposes that individual productivity is a function of ability and the individual's motivation to achieve one's goal. Other authors such as Locke et al. (1978) and Seijts et al. (2005) propose the same. We include in our framework both motivation and ability (i.e. skill level) as the antecedents of workers' performance.

Turning our focus to motivation, we must first recognize that there are several definitions of this concept. For example, motivation is defined by Vroom (1964) as "a process of governing choice made by persons", while Atkinson (1964) defines it as "the contemporary influence on direction, vigor and persistence of action". These, and other definitions, according to Steers et al. (2004), have the common notion that motivation is concerned with factors that energize, channel and sustain human behavior over time. Hence, by definition, a link between a worker's motivation and the worker's action exists, whereby motivation is a necessary pre-condition for work.

By conceptualizing motivation as a decision process Vrooms' definition (1964) lends itself to modeling where specific outcomes are ranked in terms of preference and actions are selected to obtain the most preferred outcomes. By considering motivation as a decision process, choosing among a range of possible effort levels may be modeled, just as it is done in the field of economics (Mueller, 2004). In this way, a direct implication of Vroom's definition is that motivation can be modeled as a decision process and thus defines an appropriate platform for modeling in operations management contexts (see for example the modeling choice framework proposed by McFadden (2001)). Considering this definition of motivation, we may conclude and recommend the following in modeling motivation factors:

**Modeling research recommendation 1** *Given that motivation is an antecedent for productivity and that it governs the choice of effort by workers, it should be modeled if different operational policies produce a differentiated impact on motivation.*

At the same time, several theories are available for modeling motivation. These theories range from need theory (Maslow, 1954 and Alderfer, 1972),through expectancy theory (Vroom, 1964), to goal setting theory (Locke and Latham, 1990) and self-efficacy theory (Bandura, 1997). Indeed, there is a call for integrating these motivation theories in the behavioral sciences (Locke and Latham, 2004) as these are considered as superabundant (Steel and König, 2006). For a review of all these theories, their advantages and drawbacks, we refer the reader to Latham (2007).

A few of these motivational theories often address one particular motivational theory. For example equity theory (Adams, 1965) studies fairness considerations in motivation and demotivation and goal setting theory addresses the motivational implications of assigning goals (Locke and Latham, 1990). Specialized theories of motivation can then be used to describe and model a particular motivational driver. For example, equity theory may be best used to explain and model the effects of fast workers slowing down to match the work pace of their peers (Schultz et al., 2010). This leads to the following recommendation:

**Modeling research recommendation 2** *In modeling an specific motivational driver of an operations management model, it is important to consider the use of specialized theories of motivation that may directly address an specific motivational driver. For example, the use of equity theory to model interaction between workers within a production line.*

Nonetheless, when more than one motivational drivers interact, a general framework is needed to integrate more than one motivational source. For this reason, we propose using Vroom's (1964) expectancy theory as a platform for our integrated framework of individual performance. Expectancy theory describes the process of selecting a course of action where alternative courses of action are evaluated similarly to rational gambling choices: 1) what is the probability a given action results in a number of outcomes ($E$) and 2) what is the value of such outcomes (Vroom, 1964), ($V$). By multiplying both probability and value of outcomes and summing up all the possible outcomes, the subjective expected value of a given course of action is derived. Thus, this theory is similar to rational expectancy theory used in economic modeling. Although rational expectancy theory has been criticized for diverging from the actual non-rational decisions found in practice (Albanese, 1987), this criticism can be mitigated by modifying the theory accordingly. One such modification is the incorporation of deviations for rationality as proposed by Akerlof (1991) and Steel and Koning (2006). Hence, the use of Vroom's (1964) theory allows us to characterize the relationships that link decisions to individual performance that can, at a later stage be incorporated in operations management models.

In this way, our framework depicted in Figure 2.1 starts with the relationship between effort exerted by the worker and individual performance (depicted by arrow 1 in Figure 2.1). While we can operationalize individual performance as productivity, we can operationalize effort as metabolic energy spent and cognitive load. The relationship depends on the characteristics of the task and the ability of the worker to transform effort into work (Paas et al., 2003). In highly repetitive, routine work, such a relationship is strictly increasing and relatively certain. If this is the case as it is in the majority of "blue collar" work in production and service systems, the modeling of the effects of operations management variables in individual behavior is largely simplified. For this reason, in the next sections, we assume work environments where the relationship between the individual effort and performance is quite certain and predictable.

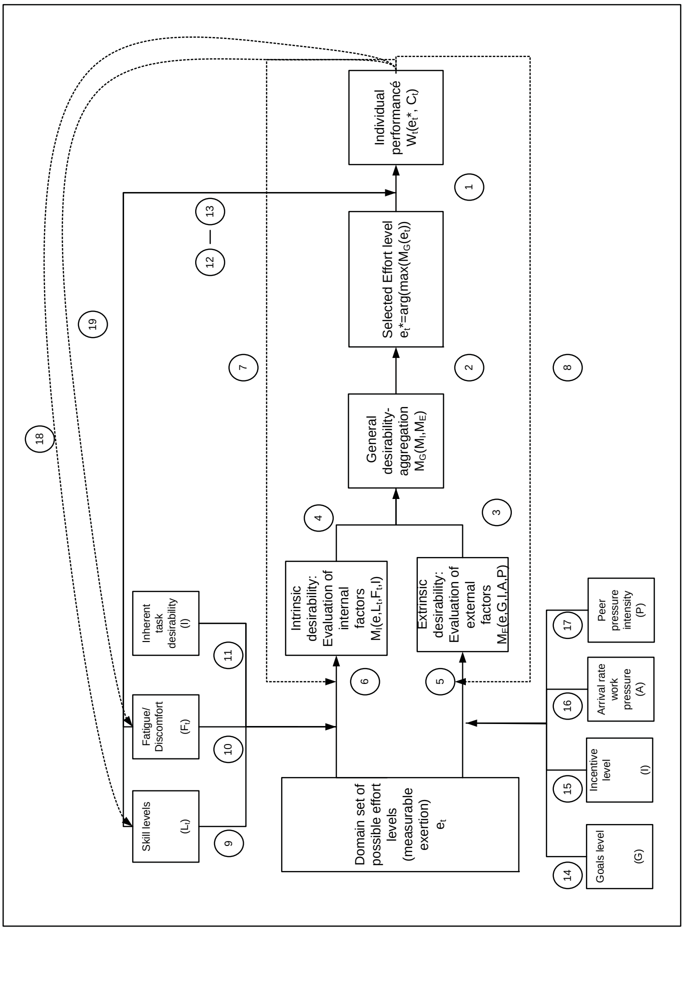



Figure 2.2: Framework for modeling worker-specific factors related to performance

However, for cases where the relationship between effort and individual performance is uncertain or even ambiguous (i.e. individual performance is difficult to measure), the evaluations of how perceived uncertainty and ambiguity play a role in the worker's decision to select his level of effort as well as strategies to perform his work. The literature on judgment under uncertainty (see Kahneman et al., 1982) has documented many departures of how uncertainty is evaluated by humans as opposed with the "rational" axiomatic approach found in most economic and operations research models of uncertainty. Moreover, for more complex work, complex cognitive decision making is required and thus falls off the scope of this chapter.

Consistent with expectancy theory, our framework conceptualizes a level of effort as a deliberate choice by the workers. Such a choice is the result of selecting the level of effort that maximizes a desirability measure (depicted by arrow 2 in Figure 2.2) or put in economic terms, the utility derived from working at a given effort level. In this framework, the use of expectancy theory is advantageous as it allows one to describe the desirability for a *range* of possible effort levels rather than just having a simplistic model in which more motivation equals more performance. Such utility is in turn derived from two different types of motivational sources, namely intrinsic and extrinsic sources (depicted in Figure 2.2 by arrows 4 and 5 respectively). This distinction of motivational sources is used widely in motivation theory (Ryan and Deci, 2000) and was first made by Vroom (1964).

Intrinsic motivation factors are factors inherent to the task itself while extrinsic motivation factors lead to separable, instrumental consequences in achieving the task at hand such as incentives or goals (Vroom, 1964). Following the expectancy theory approach, we conceptualize that for intrinsic and extrinsic motivation factors, functions exist that relate a set of alternative levels of effort and a desirability measure (depicted in Figure 2.2 by arrows 5 and 6 respectively).

In Sections 2.3.1 and 2.3.2 we discuss intrinsic and extrinsic motivational factors that can be influenced by operations management variables and that moderate the relationships between possible effort levels and their desirability. For modeling purposes, we note that these factors may be modeled directly by linking them to individual performance without establishing an internal decision making process indicating which effort level to select. However, as will be described in detail, when these factors interact with each other, a utilitarian approach may be

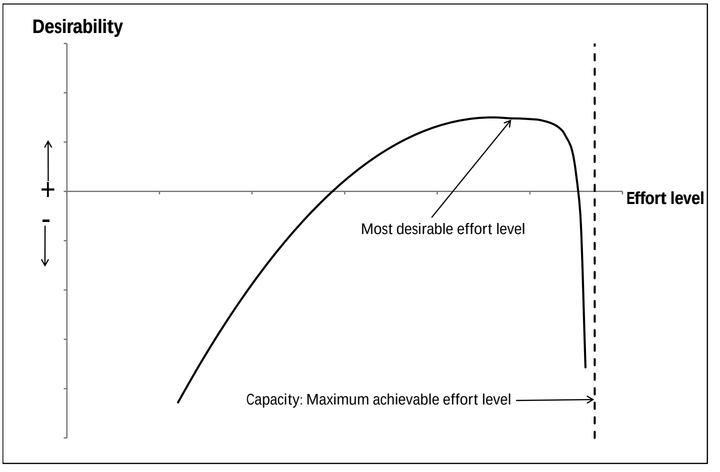



Figure 2.3: Inverted U relationship between effort and utility

the best for making predictions. We also consider, in our framework for modeling individual performance, the role of feedback regarding past performance. This feedback is likely to change the existing relationships between possible effort levels and desirability levels as depicted by arrows 7 and 8 in Figure 2.2.

### 2.3.1 Intrinsic motivational factors

The evaluation of intrinsic motivational factors relates a level of effort (e.g. work pace) with a utility measure (or effort desirability) indicating the intrinsic preference for such a level. To characterize this function, we may use a non-monotonic function where a most desirable level of effort exists forming an inverted U relationship (see Figure 2.3). The inverted U shape is justified by the combination of two effects. The first effect is the stimulation that a higher effort level provides — avoiding boredom and monotony. The second effect is the cost of a higher level of effort — including discomfort and fatigue. These costs dramatically increase as the worker exerts effort to the limit of his capacity. The combination of positive and negative effects associated with increasing the effort in a task allows for the identification of a most desirable level of effort as depicted in Figure 2.3.

The inverted U relationship can be found in the literature, beginning with a similar proposal known as the Yerkes and Dodson Law (1908) where a given level of a stressor is related to a performance level. Note the similarity between both concepts. The stressor level is similar to the effort exerted, whereas motivation is closely linked to performance, being the antecedent of performance itself. The inverted U relationship between stressor and performance has also been reported in the literature of ergonomics (Hancock, 1986), operations management (Bendoly and Prietula, 2008) and marketing (Singh, 1998).

Next, we identify skill levels (depicted in Figure 2.2 by arrow 9), fatigue and discomfort (depicted in Figure 2.2 by arrow 10) as contributing factors to intrinsic motivation that a manager can influence. Actions such as selection of personnel, training and task rotation may influence the skill level of a worker. Other actions, like resting or changing the layout may impact fatigue and discomfort. Task variety as well as task significance (as perceived by the worker and/or others) may also influence the inherent desirability of a task and thus the intrinsic motivation of the task (depicted in Figure 2.2 by arrow 11). These task and contextual factors also influence the workers' satisfaction with the job and thus will be described in Section 2.4.

**Skill level**

Although the term skill level or ability level may have different meanings, for the purpose of this chapter and thesis, we define skill level as the maximum productive capacity of an individual for a given task that can be sustained for a given period. Thus, by definition as in the case of motivation, skill level has the potential to affect worker productivity as it has been documented by Locke at al. (1978). Given this definition, the skill level is task dependent and is a reflection of the mental and physiological capabilities of a worker as applied in executing a task. Different jobs put different demands on the mental and physiological capabilities of the worker. Thus, skill level is defined as a composite maximum capacity to perform the job. For productive systems this capacity can be operationalized as the maximum attainable number of jobs processed per hour assuming a constant and sufficient quality level.

Nonetheless, a higher skill level may not necessarily translate into a higher productivity level (Bendoly and Prietula, 2008). Workers may be not be motivated enough to exert effort to the limits of their ability. This motivation is needed as working close to the skill level may be not be desirable in the absence of external motivators. Skill level does however, affect productivity in two ways: one by defining a boundary condition on the maximum performance possible, thus moderating the relationship between effort levels and actual performance (depicted in Figure 2 by arrow 12) and two by moderating the relationship between intrinsic motivation factors and effort level (depicted in Figure 2.2 by arrow 9). Using the inverted U relationship, skill levels may be modeled as moderating this relationship by shifting the most desirable effort level to higher effort levels as documented by Bendoly and Prietula (2008). In other words, if the skill level is increased (decreased) the most desirable effort level increases (decreases). Hence, we recommend:

**Modeling research recommendation 3** *In modeling conditions where varying skill levels and external motivational forces (e.g. work pressure, assigned goals) exist, skill levels should not be assumed to automatically result in increased performance, but rather to moderate the inverted U shape relationship between the level of effort and effort desirability (i.e. the intrinsic motivation relationship). In addition, the skill level sets the maximum performance attainable as a boundary condition.*

The main levers that an operations manager has at his disposable to directly influence the skill level of its workforce are learning and forgetting processes (Nembhard and Uzumeri, 2000). These are arguably (particularly the former) the most studied and modeled human-factor processes in operations management. While Yelle (1979) and Belkaoui (1989) provide an overview of different alternatives in modeling learning processes, Argote (1996) provides an overview on modeling forgetting processes. Given the wealth of alternative learning curves, Nembhard and Uzumeri (2000) recommend the use of a hyperbolic model of learning because it performs best under two criteria. First, it fits individual empirical data best. Second, it contains interpretable parameters. While the traditional log-linear model also provided reasonable fits, it only fits a more narrow range of empirical learners. In Shafer et al. (2001), the hyperbolic model was extended to accommodate forgetting processes as well, fitting empirical data adequately.

In all of the learning models the key variable that may be influenced by different operations management policies is cumulative output (or time spent at the task), i.e. "learning by doing", whereas for forgetting models it is the time elapsed since the last item was produced. This dynamic dependency is depicted in our framework by arrow 18 in Figure 2.2.

In addition to operations management variables influencing the time available for learning and forgetting processes, operations management variables may also influence learning and forgetting rates. While Adler and Clark (1991) have studied the effects of training programs and engineering interventions (e.g. technological, equipment and process interventions) in learning rates, Nembhard (2000) studied the effect of task complexity as a determinant of learning and forgetting rates. These are examples of drivers of learning and forgetting rates that may be influenced by operations management decision variables, however the current list is not exhaustive and the study of other factors of learning and forgetting rates (e.g. learning from the experience of others, available feedback, use of learning goals) is an opportunity for further research.

Another aspect that needs to be acknowledged in modeling the effects of workers' skill levels is the heterogeneity of skill levels. In the operations management literature, it has been recognized that individual variation in work rates can have an important impact on the productivity of a productive system (see Juran and Shruben (2004) and Doerr and Arreola-Risa (2000)). Furthermore, Shafer et al. (2001) also provide evidence that heterogeneity in learning rates can have an important impact on system productivity. In particular, the average production with learning heterogeneity is greater than the production of an average learner, given that the production rate is increasing and concave. Operations managers may influence heterogeneity of skills and learning rates indirectly by the selection of personnel.

Summarizing, we recommend the following in modeling skill levels in operations management decision models:

**Modeling research recommendation 4** *The following aspects need to be considered when incorporating skill level in operations management decision models: 1) Learning and forgetting processes that are mathematically described in the literature; 2) Factors that affect learning and skill rates (besides experience) that can be influenced by operational variables such as task* *complexity and periods of training; 3) Variability of skill levels as well as learning and forgetting rates due to heterogeneity in the population.*

Further empirical research may also enrich current models of learning and forgetting in operations management. Thus, we recommend the following:

**Empirical research recommendation 1** *The study of other OM controllable factors of learning and forgetting processes is an opportunity for further research. In particular, learning from others, learning given different types of feedback and the use of setting goals for learning require still further exploration and description to be included in existing OM models.*

**Fatigue and discomfort**

"Fatigue" is generally defined as a "reduction of the functional capacity of an organ or an organism as a result of an action", Rohmert (1973). Hence, by definition, fatigue further limits, albeit temporarily, the maximum productive capacity of individuals in a manner similar to forgetting processes by reducing the skill level. As with skill levels, this moderates the relationships of effort levels and performance (depicted in Figure 2.2 by arrow 13). Nonetheless, fatigue also has a second effect on performance via motivation (depicted in Figure 2.2 by arrow 10) as it has been found to lessen the "will to work" (Das, 1990, Taris and Schreurs, 2009 and Van Yperen and Hagedoorn, 2003). Simultaneously, fatigue is built up over time due to past exposure to effort (Bechtold and Sumners, 1998). Our framework captures this dynamic dependency with arrow 19 in Figure 2.2.

Empirically, the relationship between fatigue and productivity is complex. Fatigue has been modeled in operations management by assuming a linear decay throughout the day (Bechtold et al., 1984). Such an assumption based on the empirical work by Janaro (1982) where subjects are asked to accomplish an exhausting ergometer task and the working rate is shown to decrease linearly. In a similar vein, Paarsch and Sheaer (1997) find a linear decay in performance in a physically exhausting tree-planting task, however we note that this linear decay is only observed *across* working days at a rate of 3-5% productivity per day, but not within days. However, in Okogbaa (1983), an exponential decay in productivity was found. Furthermore, interventions, such as changing work-rest schedule, show that fatigue may be reduced with simultaneous improvements in productivity as found in visual-display work (Kopardekar and Mital, 1994) and typing work (Balci and Aghazadeh, 2003).

Also important to modeling the effects of fatigue in productivity is a task-specific approach in order to identify the limiting factor affecting performance or exposing workers to unacceptable health risks. Fatigue can take several forms as detailed in Price (1990) where the following categories are suggested: general metabolic fatigue, muscular fatigue and mental fatigue. General metabolic fatigue refers to a reduced capacity of the body's aerobic system, producing tiredness (Murrell, 1965). Muscular fatigue, on the other hand is when a group of muscles has been excessively exerted with loads and experiences a reduction in functional capacity (Rohmert, 1973). Mental fatigue can take many forms; but, in general, it is translated into a decrease in the operational performance of the mind, including attention and problem-solving capacity (Schmidtke, 1976). Any of these dimensions of fatigue may affect fatigue in general; that is, a reduction in the "functional capacity of an organ or an organism" and thus a temporal reduction of "skill level".

The works of Konz (1998), Mital et al. (1991) and Price (1990) all provide mathematical descriptions of how to determine rest allowances by modeling the accumulation of fatigue while taking into account the avoidance of health problems and significant decrements in performance. Interestingly, whereas metabolic fatigue is modeled to accumulate linearly, local muscle and mental fatigue are assumed to grow exponentially (Mital et al., 1998). Although these models of fatigue build-up are available, a clear description of the determinants of fatigue rates depending of the type of fatigue (mental, localized for an specific muscle group) is still incomplete, including work intensity, the influence of durations of resting periods and types of rests (e.g. sitting, standing), the addition of micro-rests and thus we recommend the following:

**Empirical research recommendation 2** *For including fatigue in operational models more explicitly, it is important to have a more clear understanding of how fatigue builds up for spe-*

*cific types of fatigue and how other factors may influence such build-up process (including work intensity, the duration of resting periods, type of rests and micro-rests).*

Across days, circadian rhythms (i.e. the fluctuation of physiological conditions governed by the Earth's day-night cycle, Wickens et al., 2004) become important. In particular, empirical studies have linked common shift-work decision variables with several physiological measures related to fatigue (Czeisler et al., 1982; Knauth, 1996; Kostreva at al., 2002; Hsie et al., 2009). Among the shift/work decision variables studied, shift duration, starting time, direction of shift rotation, days/night shift and distribution of days-off appear to be most important in influencing fatigue and circadian disruption. Moreover, a meta-analysis exists (Spencer et al., 2006) in which fatigue and related risk indexes are derived comparing the incidence of accidents and fatigue measures (measured as micro-sleep periods) given a number of shift scheduling variables.

Summarizing, when considering fatigue as a factor in a decision making model, it is important to take a context-specific approach to determine which aspects of worker well-being are affected by fatigue.

**Modeling research recommendation 5** *In incorporating fatigue effects in operations management models the following effects may be incorporated*: *1) Performance deterioration modeled through a temporary decrease of "skill levels"; 2) Fatigue accumulation (measure of well-being); 3) Risk of accidents.*

In addition to fatigue, a related, but distinct concept that can potentially affect the costs of performing a job at a given effort level is discomfort. Discomfort is in fact a physiological measure of how an individual perceives their exertion and was first introduced by Borg (1982). Similar to fatigue, discomfort may increase over time. The advantage of such a measure is that instead of providing an objective physiological measurement such as the "maximum voluntary contraction" of a muscle, the subjective discomfort measurement already incorporates an integrated judgment of all such objective conditions and thus indicates the individual's evaluation of the adequacy of a current physical situation (Dul et al., 1994). Hence, as with the case of fatigue, discomfort influences the perceived desirability of a given effort level and thus possibly individual performance. Nonetheless, the nature of such a relationship is not yet well understood. What is known however, is that discomfort is a predictor for future long-term muscular pain (van Reenen et al., 2008) as well as occupational disorders, such as the so-called Low Back Disorders (LBDs). Thus, discomfort is valuable in itself by being a current physical situation and because its associated benefits for health. However, the link with performance remains to be clearly established and thus we recommend the following:

**Empirical research recommendation 3** *For including discomfort in operational models more explicitly, it is important to study the role of discomfort as a factor that affects motivation and, in turn, performance. A clear description of such a mechanism is not available and needs to be revised for different types of tasks, work intensity and work-rest periods.*

### 2.3.2 Extrinsic motivational factors

Unlike intrinsic motivational factors, the evaluation of extrinsic motivational factors may take different forms given the wide range of factors at play. Hence, the approach to model them may not be unique. Nonetheless, all of these extrinsic motivators have in common that they increase the perceived benefits (i.e. rewards) or lack of benefits (i.e. punishments) associated with performing a job by altering the consequences of performing that job. In the literature relevant for operations management, there is evidence for both, motivational interventions and de-motivational interventions with significant effects of up to 50% as noted by Bendoly and Prietula (2008). In this sub-section, we review a few of the motivators that may be used directly by operational managers to enhance individual performance. In particular, we review assigned goals, incentives, job arrival rate and peers' influence (depicted in Figure 2.2 by arrows 14, 15, 16 and 17 respectively).

**Assigned goals**

The assignment of specific, usually quantitative goals has been the prime subject of goal setting theory (Locke and Latham, 2002a) which has been widely studied and validated in the field and in laboratory studies. The type of goals studied include productivity, quality and learning goals (Locke and Latham, 1990). The basic tenant of goal-setting theory is that challenging goals improve performance thereby proving to be an effective contributor to extrinsic motivation (depicted by arrow 14 in Figure 2.2). A meta-analysis shows strong effects compared to telling individuals to "do their best" (Locke and Latham, 1990). The reported effect sizes, i.e. the ratio between the mean increase of performance (i.e. $\Delta\bar{x}$) and standard deviation (i.e. $s$) of the data in the study (i.e. $d = \Delta\bar{x}/s$) ranged from $d = .42$ to .80.

The four mechanisms by which goals have been found to affect performance (Locke and Latham, 1990) are: 1) Goals direct attention and effort toward goal-relevant activities and away from goal-irrelevant activities; 2) Higher goals lead to greater effort than low goals; 3) Goals affect persistence; 4) Goals affect action indirectly by leading to the arousal, discovery, and/or use of task-relevant knowledge and strategies.

As long as there is commitment towards the goal (i.e. "one's attachment to or determination to reach a goal, regardless of the goal's origin", Locke et al., 1988), the relationship between goal difficulty, measured as percentage of the population that are not able to attain the goal, and performance is non-decreasing, leveling-off at the limits of ability (i.e. skill level) (Locke and Latham, 1990). When commitment to the goal fails due to unrealistic goals, performance drops with greater goal difficulty (Erez and Zidon, 1984).

In production system contexts, goals have been translated in terms of "number of jobs to be completed per unit of time" (Doerr et al., 1996) or "number of jobs to be completed before a deadline" (Chapters 3 and 4 of this thesis). Doerr's (1996) study analyzed a production line and found that in such a line, group goals enhanced performance more than individual goals. The empirical study presented in Chapter 4 of this thesis confirms that performance increases with an increasing goal, leveling-off when the skill level of an individual is achieved. Furthermore, the study in Chapter 4, finds that challenging goals induce workers to perform at steady speeds at the best of their ability.

**Modeling research recommendation 6** *When varying goal levels are used as a decision variable in an operations management model and when it is assumed that workers are committed towards the goal, then a strictly non-decreasing function, where performance levels-off at the limit of ability should be used to model individual performance.*

Further investigation of a mathematical description for goal setting has shown that goals may be taken as a reference point to evaluate other levels of performance. In particular, a study by Heath et al. (1999) and another described in Chapter 4 of this thesis shows that the evaluation of goals can be modeled using the "S"–shaped evaluation function of Kahneman & Tversky's Prospect Theory (1979). This function exhibits the following properties (see Figure 2.4): 1) Goals are used as reference points to evaluate personal performance; 2) Evaluation of performance is most sensitive around the goal; 3) Underachieving the goal (a "loss" in Prospect Theory language) looms larger than over-achieving the goal (a "gain" in Prospect Theory language).

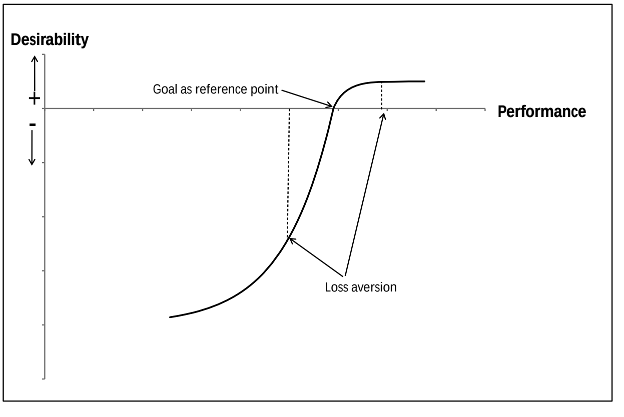



Figure 2.4: Evaluation of performance under the influence of goals function

It is also important to remark here that the effect of productivity goals on quality remains to be investigated in operational contexts. This is particularly important when considering reports that productivity goals tend to attract attention at the expense of achievements along other lines and in contexts where no goals have been set (Locke and Bryan, 1969). In this respect, a study in the operations management literature (Philipoom and Fry, 1999) illustrates that goals on selective performance criteria may be affected by a "cherry picking" phenomenon where workers select the orders that maximize their individual performance at the expense of system-wide performance.

In addition, the interaction of assigning goals specific attributes that are pervasive to operational contexts should be studied. One of the main attributes of work in operational contexts is whether the work is performed in an individual setting or, most commonly in a group setting. The studies of individual versus group goals in Doerr (1996) require further exploration, beyond the result that group goals are more effective in task-dependent production lines than individual goals. Research is needed to address the issues of feedback from other individuals at the production line for achieving the goal and convenience of setting goals given constrained resources. Already, a study by Vijfeijken et al. (2002) emphasizes the need of designing multiple goals and rewards that mimic the interdependence found in productive environments so as to boost system performance by providing incentives for individual performance and group performance.

Another important attribute of operational contexts is the fact that people tend to work for weeks, months even years at similar jobs. If different goals are repeatedly set over time, accounting for variability in the demand, it is important to be able to characterize goal adaptation processes. In these contexts, experience of previous performance with goals may affect future performance under goals. It is already known that self-set goals are adjusted by previous performance (see Lant, 1992 and Mezias et al., 2002), however it remains unknown as to how performance is affected if the goals are assigned by managers and vary over time. Hence, for empirical researchers, we recommend the following:

**Empirical research recommendation 4** *A research agenda on goal setting already exists (see Latham and Locke (2007)), however such a research agenda should be adapted to the needs of operations management contexts, where interdependencies between workers and the repetition of goals are important.*

**Incentives**

The literature on the effects of performance with both monetary and non-monetary incentives (in the form of prizes, public recognition) for motivating performance is extensive, however their effects on performance are disputed. For this reason, it is useful to make use of meta-analysis studies. We refer the reader to two of them, that of Jenkins et al. (1998) and that of Condly et al. (2003) which find an overall average effect of a 22% increase in performance over control groups. Further, the latter meta-analysis study finds a number of factors that may enhance the positive effect of incentives. In particular, Condly et al. (2003) find that: 1) Monetary incentives have a significantly larger effect than non-monetary ones; 2) Team rewards seem to yield higher results than individual rewards; 3) Incentives for manual work have a larger impact on performance than incentives for cognitive work; 4) Incentives have a larger effect on inducing increased cognitive and physical effort than on encouraging people to start a new job.

Despite the fact that there is a positive (and differentiated) effect of the aforementioned factors, the functional relationship between incentives and performance remains unknown and proves to be complex. Although there are econometric studies of field data that show a positive impact on performance with piece-rate incentives (see Paarsch and Shaerer (1999) and Lazear (2000)) as well as experimental evidence for this (see Campbell (1984) and Huber (1985)), it is first necessary to verify how much the monetary incentives are really worth for the participants involved. This question arises as the result of a few studies reporting that monetary incentive schemes have no-effect, presumably because such rewards were considered as insufficient or even unfair (Condly et al., 2003).

Another complexity of the use of incentives are the interaction effects obtained when used with goals. In this way, there is evidence that monetary incentives can increase goal commitment, but at the same time inhibit the attainment of complementary goals which are not compensated, such as helping their peers at the workplace (Wright et al., 1993). Note that goal commitment implies a decision of whether or not to attempt goal attainment, thereby influencing performance, but not the goal set. This clearly contrasts with the piece-rate reward system that is independent of the goal set and which rewards a partial accomplishment of the goal (Locke et al., 1988).

The complexities described of the effects of monetary incentives imply that given the current knowledge, it is easier to incorporate the effects of goal assignment into a model than it is to incorporate (non-) monetary incentives. Thus, we observe the following:

**Empirical research recommendation 5** *Incentives, as extrinsic motivation factors, have complex relationships with motivation and performance. Moreover, such relationships may be context dependent and thus prior empirical work may be required before modeling the effect on performance of specific incentives in specific contexts.*

**Job arrival rate**

The job arrival rate is an operationalization of work pressure; workers are expected to cope with the job arrival rate. In a sense, setting higher quantitative production goals can also be operationalized as work pressure. However, production goals are distinct in nature because they are meant for "challenging workers" rather than a metric for the workload assigned to workers. In this respect, Bendoly and Prietula (2008) find an increasing and then decreasing relationship between work pressure and performance. Moreover, Bendoly and Prietula (2008) find also an increasing and then decreasing relationship between work pressure and motivation. Their empirical results support previous studies that also find an increasing and then decreasing relationship between work pressure and performance (Leibenstein, 1984 and Suri and De Treville, 1986). Hence, the following recommendation may be made for modeling the effect of different job arrival rates on performance:

**Modeling research recommendation 7** *In OM models, the arrival rate–performance relationship should be modeled as increasing and then decreasing given the empirical evidence available.*

However, such relationships are in the end a composite effect of two forces as explained by Bendoly and Prietula (2008). The first one is the evaluation of the intrinsic benefits of the task and the second one is the evaluation of the extrinsic benefits of the job. While for the first one we may apply the inverted U relationship of Yerkes' and Dobnson's Law (1908), as previously discussed, the second one is more unclear. For sure, the maximum attainable result is a matching of the job arrival rate with the job processing rate, meaning that a non-decreasing function linking effort level and (extrinsic) desirability is in order for this kind of work pressure. What remains unknown, is if such a job arrival rate acts as a reference point in the same manner as with goal setting. One may hypothesize that it does and that hence, the desirability (and motivational) gain of closely matching the job arrival rate is greater the closer the job arrival rate is to the current job processing rate.

It should be noted that unlike goals for which performance is evaluated at the end of an assigned period, the objective linked with varying job arrival rates is the clearance of the queue — thus performance is continuously monitored. If, for example, a worker can not match the job arrival rate within a small margin, the queue will increase indefinitely. Even temporary, mismatches in the job arrival rate may increase the variability of queue lengths which accumulate over time (Kleinrock, 1975). As a result of large queues, workers may be less committed to match the job arrival rate and settle for lower job processing rates. This hypothesis should be verified empirically. Hence, opportunities for future research exist in comparing the effects on individual performance with work pressure and with specific goals and deadlines in comparable conditions.

**Empirical research recommendation 6** *The comparison of performance and satisfaction of workers under work pressure and goal setting provides an opportunity for research that could be incorporated into models for selecting an appropriate extrinsic motivation strategy under a number of conditions (e.g. dependency between workers, acceptable makespan times).*

### Peer pressure

The effects of peers were a main concern in early modern work regarding the interface of operations management decisions and individual performance (Boudreau et al., 2003). The work of Schultz et al. (1998) found, for example, how workers in a flow line attempted to avoid their upstream colleagues becoming idle due to blockage in the production line by accelerating their work pace. This implied a new advantage of low inventory systems (i.e. Just In Time systems) over high inventory systems, as in the former, blockage occurs more often, and thus, workers may tend to produce at higher production rates.

Further investigation has been made regarding how "fast workers" tend to slow down in the presence of "slow workers" and vice-versa. Schultz et al. (2010) argue that this is consistent with equity theory which predicts a regression toward the mean of performance as workers attempt to match their peers' performance (Adams, 1965). Also disparity in personalities has been found to have an effect in work sharing environments such that more dominant personalities tend to use shared resources more often than their dominated counterpart (Juran, 1997). Hence, difference of personalities may moderate the peer induced motivational drive. Given the current knowledge, the following recommendation may be useful in accounting for peer induced motivation:

**Modeling research recommendation 8** *Equity theory, modeled as a regression towards the mean of performance by workers, can be used to model serial productive systems by taking pairs of upstream–downstream workers.*

In addition, when teams are to be formed, it appears that perceived similarity among workers is desirable for enhancing team cohesion and also performance (Knippenberg et al., 2004). This is significant for operational contexts where the interdependency among workers is high and constantly changing over time, as is the case, for example, in cell manufacturing environments. In fact, Schultz et al. (1999) found that in low inventory systems where the interdependence of individuals is greater, cohesiveness is more significant. Thus, in the assignment of workers to available working teams, social aspects ought to be considered. However, these social interaction aspects need to be considered for specific production contexts, where design aspects of such production contexts (e.g. layout, work sharing rules, worker-station assignments) may affect how the interaction between individuals occurs. Hence, we recommend the following for model-oriented empirical research on the influence of peers' in the workplace:

**Empirical research recommendation 7** *More research is required regarding complex social interactions between workers for specific production system contexts. Helping among workers, learning from others, and work sharing are all subjects that need further research for incorporation into existing operations management models.*

### 2.3.3 Feedback

Individual performance feedback in production systems may take several forms. It may be given as an accurate measurement of the performance metric used for the worker's job appraisal or as a proxy of such (e.g. queue length in front of the individual server). The feedback provides information of past individual performance, this is depicted in our framework with arrow 11 in Figure 2.2. Feedback is essential for informing both, the evaluation of intrinsic and extrinsic motivation factors (depicted in Figure 2.2 by arrows 7 and 8). In addition, feedback is important for devising a strategy of work to reach the personal desired performance.

The importance of feedback design is highlighted as it has been recognized as a necessary condition for goals to affect performance (Erez, 1977). In fact, in Schultz et al.'s (1998) study of low inventory serial lines and Bendoly and Prietula's study of work load (2008), feedback in terms of job arrival rate and queue length provided the experiment participants with the necessary information to adjust their workload accordingly. Moreover, Schultz et al. (2003) find a positive effect on performance when enhancing feedback in work sharing environments: workers tend to be more motivated by their peers when they perceive that their own performance is more visible.

Feedback design has been analyzed in the ergonomic literature (see Karwowsky (2006) for a compilation of articles in the subject). For production system contexts however, questions remain as to how to design feedback in terms of frequency, metrics (a proxy of a real operational performance measure) and framing (e.g. 20% of time remaining to deadline vs. 80% of time has elapsed), particularly in conjunction with other operations management variables already addressed (i.e. goal, job arrival rate). Of interest is the study of Amir and Ariely (2008) which finds that it is not necessarily the case that continuous feedback and the addition of progress indicators (i.e. milestones in the form: "you reached x% of the goal") enhance performance. Amir and Ariely (2008) argue that a possible reason for this is the deceleration that often occurs after a milestone is achieved. Hence, given the scarce information on how to design feedback for productive systems, we find it a relevant to topic to be researched for the advancement of operations management theory.

**Empirical research recommendation 8** *More empirical studies are required on incorporating feedback design variables (e.g. information presented, frequency, framing) in operations management decision models.*

Having surveyed worker specific factors that operations managers may influence to enhance performance, we know consider in the next section those factors that the manager has influence to enhance the job satisfaction of a worker.

## 2.4 Job satisfaction

In this section, we use Weiss' (2002) definition of job satisfaction as a "positive (or negative) evaluative judgment one makes about one's job or job situation". In the literature on job satisfaction measurement, a debate exists as to whether job satisfaction should be measured as a single measurement or as an aggregation of several aspects of the job called facets of job satisfaction (see Weiss, 2002 and Scarpello and Campbell, 1983). It remains unknown whether all the facets of satisfaction have been identified in the literature and how to integrate them. In fact, the integration of job satisfaction facets may be context dependent. A physical job such as lifting boxes may have different facets that are considered important as compared to a job that stresses fine coordination like an assembly job. Therefore, the state of the art in job satisfaction is limited to measuring the impact of job satisfaction aspects as an overall measure of job satisfaction. At the same time, operational decisions, usually only have an impact on a limited number of job satisfaction aspects. Hence, we recommend the following in formulating the objectives of operations management:

**Modeling research recommendation 9** *In incorporating job satisfaction related objectives, only a single (or very few) relevant facets of job satisfaction should be explicitly modeled as an objective(s).*

### 2.4.1 Conditions for selecting job satisfaction facets

For empirical researchers, a call exists to provide a clearer picture on how workers develop positive and negative attitudes towards their job and how different facets of job satisfaction are integrated. For our purposes, however, the concern is how to select the relevant job satisfaction facets for operations decision models. To achieve this, we first identify relevant job satisfaction facets that have been proven to be linked to overall job satisfaction and that can be influenced by operations management decisions.

This definition of relevant job satisfaction facets implies, first, that the facet of job satisfaction needs to be operationalized in a meaningful way. For example, a facet of job satisfaction may be safety at work. This may then be operationalized as the probability of an accident weighed by its probable severity (i.e. accidentability). The objective may be then to minimize the accidentability of a job. Second, the definition implies that the model's objective needs to be linked to the decision variables of the model at hand. Differences in the levels of the decision variables must be reflected in differences in the levels of the objective function.

Although this is an obvious point, and is valid for any model in operations management, the implications are not trivial as it means that a relation must be established between both. Take for example the case of the need for autonomy at the job. Certainly, subjective scales exist for measuring autonomy at the job in terms of methods, schedule and decision making. The difficulty is to link particular job satisfaction facets with operational variables. If, for example, the decision variable is the assignment of workers to blocks of schedules with each block of schedules containing schedule options that the workers can choose from. As a result, there is the need for a linking operational variable to serve as a proxy for a job satisfaction facet. One such linking variable for the case of worker's autonomy with schedules may be the number of options available within a block of schedules for the worker to select his working schedule. The challenge still remains in relating such linking variables with the job satisfaction facet. This linking process is a challenge as the effects of a particular operational policy may only be possible to observe in the long term. This challenge can be addressed by either using existing documented empirical relationships or quite likely new empirical studies are required.

Summarizing, we conclude that the following are necessary conditions for including job satisfaction related objectives in operations management decision models:

**Modeling research recommendation 10** *To include a facet of job satisfaction as an objective in operational models two conditions must be met: the facet needs to be operationalizable and different levels of the operations management decisions must induce different levels of the operationalized objective. To meet the latter condition, linking variables that serve as proxies for job satisfaction facets may be needed. It may also be necessary to conduct further empirical studies to link the proxy variable to the desired facet of job satisfaction.*

Although we acknowledge that such conditions must hold for any operations management objective in general, this recommendation is of particular significance for operations management models which are often criticized for not incorporating several worker–specific factors, ignoring the fact of whether it is feasible or relevant to incorporate them.

### 2.4.2 Identifying facets of job satisfaction

In addition to defining the conditions for including a job satisfaction facet as an objective in an operations management decision model, it is important to identify properly documented job satisfaction facets. A key question that then arises is which sources to use to identify a list of relevant facets of job satisfaction. Our approach is to draw from the contributing factors of job satisfaction identified by four representative and widely used models of job satisfaction.

In particular, we draw form the Job Characteristics Model (Hackman and Oldham, 1980), the Theory of Work Adjustment (Dawis et al., 1968), the Work Compatibility Model (Genaidy and Karwowski, 2003) and Work Design Questionnaire (Morgeson and Humphrey, 2006) to identify candidate facets of job satisfaction that are relevant for operations management. A comprehensive list of the factors included in these models can be found in Tables 2.1 and 2.2. As it can be observed from both tables, there are certain commonalities among the factors used, but also differences. In all of these facets, the operationalization can be achieved by linking likert scale responses to the statement: "I am satisfied with (e.g. the task variety) of my job" with actual measurable levels of the facets (e.g. number of different tasks that a given job requires). We proceed to briefly describe the main characteristics of these three models of job satisfaction before integrating them into one for operations management modeling purposes.

**Job Characteristics Model**

The Job Characteristics Model focuses mainly on psychological facets of job satisfaction (these are referred to as job characteristics), because these are derived from identifying three psychological states that are considered key for job satisfaction. These psychological states are: 1) The extent to which the job is meaningful for the worker; 2) The extent to which the worker feels responsible for his work; 3) The extent to which the worker is knowledgeable of his work performance (i.e. feedback is provided). The model is supported by more than 200 studies relating the psychological facets of job satisfaction and job satisfaction itself (Ambrose and Kulik, 1999). The model is then operationalized and measured using the Job Diagnostic Survey (Hackman and Oldham, 1975). The advantage of this model is the recognition of job satisfaction as a psychological state influenced by three other psychological states. However, the Job Characteristics Model has been found to consider only a narrow set of motivational job characteristics (Morgeson and Humphrey, 2006), ignoring numerous other work characteristics (Parker et al., 2001).

**Theory of Work Adjustment**

Next, the Theory of Work Adjustment is based on the basic tenant that the worker "seeks to achieve and maintain correspondence with the (work) environment" where correspondence means a "harmonious relationship between the individual and the environment" such that the "environment is suitable for the worker and the worker is suitable for the environment" (Dawis et al., 1968). The theory includes 20 dimensions that were found to be related to an overall assessment of job satisfaction. For evaluating the 20 facets of job satisfaction, the Minnesota Satisfaction Questionnaire (MSQ) was proposed (Weiss et al., 1967). The MSQ is widely used in industry, however, as some categories are rather broad (e.g. "working conditions"), these become for our purposes difficult to operationalize due to a lack of detail in the categories' specification. Furthermore, the completeness of the 20 facets of job satisfaction has also been questioned (Scarpello and Campbell, 1983).

**Work Compatibility Model**

A more precise and possibly more comprehensive list of job satisfaction facets is given in the Work Compatibility Model (WCM) by Genaidy and Karwowsky (2003). As the model comes from the ergonomic literature, it contains both physical and psychological factors. Although, the WCM is not specifically designed as a model of job satisfaction, Genaidy et al. (2007) have linked the model to individual well-fare (a more inclusive concept than job satisfaction) as well as long-term worker productivity. Central to the WCM, is the concept of fit where workers are set to match job *demands* and job *energizers* that are said to simultaneously decrease (increase) the capacity and will to do the job. In this way, task variety for example, exerts demands due to the number of skills required, while training energizes such demands by providing the means to properly execute the variety of tasks to be performed. This framework also implies that the most desirable level of a job satisfaction facet, such as task variety, may be contingent on other factors, such as the training available to perform such a variety of tasks.

**Work Design Questionnaire**

The Work Design Questionnaire (WDQ) (Morgeson and Humphrey, 2006) is a tool that measures job satisfaction facets with the specific purpose of aiding managers in the redesign of their employees' work. This objective is similar to our objective, with the difference that our objective is more limited by a focus on operational decisions that can be included in decision models. The WDQ was also specifically designed to address the lack of comprehensiveness in

Table 2.1: Facets of job satisfaction according to different models (Part I)

| Job Characteristics Model (A) (Hackman and Oldman, 1980) | | MSQ Factors (B) (Dawis et al., 1968) | |
|---|---|---|---|
| *Experienced meaningfulness of the work* | | - Ability utilization | B1 |
| - Skill variety | A1 | - Achievement | B2 |
| - Task identity | A2 | - Activity | B3 |
| - Task significance | A3 | - Advancement | B4 |
| *Experienced responsibility of the work* | | - Authority | B5 |
| - Autonomy | A4 | - Company policies & practices | B6 |
| *Production feedback* | | - Compensation | B7 |
| - Feedback from coworkers & supervisors | A5 | - Co-workers | B8 |
| - Work interdependence | A6 | - Creativity | B9 |
| | | - Independence | B10 |
| | | - Moral values | B11 |
| | | - Recognition | B12 |
| | | - Responsibility | B13 |
| | | - Security | B14 |
| | | - Social Service | B15 |
| | | - Social status | B16 |
| | | - Supervision: Human relations | B17 |
| | | - Supervision: technical | B18 |
| | | - Variety | B19 |
| | | - Working conditions | B20 |

Table 2.2: Facets of job satisfaction according to different models (Part II)

| Work Compatibility Framework (C) (Genaidy and Karwowsky, 2003) | | Work Design Questionnaire (D) (Morgeson and Humprey, 2006) | |
|---|---|---|---|
| *Organizational environment* | | *Task characteristics* | |
| - Time organization | C1 | - Work scheduling autonomy | D1 |
| - Work responsibility | C2 | - Decision-making autonomy | D2 |
| - Policies-procedures | C3 | - Work methods autonomy | D3 |
| - Task meaningfulness | C4 | - Task variety | D4 |
| - Autonomy | C5 | - Significance | D5 |
| *Technological environment* | C6 | - Task identity | D6 |
| *Physical environment* | | - Feedback from job | D7 |
| - Tools-Equipment | C7 | *Knowledge characteristics* | |
| - Immediate hazards | C8 | - Job complexity | D8 |
| - Workplace layout | C9 | - Information processing | D9 |
| - Architectural design | C10 | - Problem solving | D10 |
| - Chemical environment | C11 | - Skill variety | D11 |
| - Biological environment | C12 | - Specialization | D12 |
| *Economic growth environment* | C13 | *Social characteristics* | |
| *Individual growth environment* | C14 | - Social support | D13 |
| *Social & communication environment* | | - Initiated interdependence | D14 |
| - Conflict | C15 | - Received interdependence | D15 |
| - Support | C16 | - Interaction outside organization | D16 |
| - Openness | C17 | - Feedback from others | D17 |
| - Praise | C18 | *Work context* | |
| - Feedback | C19 | - Ergonomics | D18 |
| - Knowledge of goals | C20 | - Physical demands | D19 |
| *Mental task content* | | - Work conditions | D20 |
| - Information processing | C21 | - Equipment use | D21 |
| - Memory | C22 | | |
| - Cognitive | C23 | | |
| *Physical task content* | | | |
| - Sensory | C24 | | |
| - Strength | C25 | | |
| - Endurance | C26 | | |
| - Sudden handling | C27 | | |
| - Upper body posture | C28 | | |
| - Lower body posture | C29 | | |
| - Experienced domains | C30 | | |

previous job satisfaction measurement tools, and to update and integrate new findings related to facets influencing job satisfaction (Morgeson and Humphrey, 2006). The WDQ categorizes facets under four categories: 1) Task characteristics; 2) Knowledge characteristics; 3) Social characteristics; and 4) Contextual characteristics. This characterization is suitable for operations management contexts, as it acknowledges the domain of influence of operations management decisions.

It must be noted however, that despite an increasing awareness of the WDQ in the literature (e.g. Morgeson and Humphrey (2006) have been cited more than 50 times as of July, 2010), the WDQ is still not widely used nor widely accepted in the job satisfaction literature.

**Job Satisfaction Framework for Operations Management**

We propose a job satisfaction facets framework for operations management that is based mainly on the WDQ. However, we differ from previous frameworks of job satisfaction by selecting only facets that are likely to be linked to existing or potential operations management decision variables. For example, we exclude facets like whether the tasks provide opportunities for problem solving (see facet D10 in Table 2.2) or the amount of interaction with individuals outside the organization, as these are factors that do not pertain to the design of the task itself (see facet D16 in Table 2.2), but are more often a "given" in operational settings irrespective of operational decisions.

We classify job satisfaction facets according to the domain of operations management decisions that may be affected (see Table 2.3). In this way, we derive three categories of job satisfaction facets: 1) Facets related to the *task(s) content* of the job itself (including tasks to be performed and skills required); 2) Facets related to the *interactions* between the worker with his/her peers and supervisors; 3) Facets related to the organizational and physical *environment* in which the task needs to be performed.

Table 2.3 provides an overview of the framework, with the facets classified per category alongside their definitions. To operationalize each of the facets, Table 2.3 provides a list of related job satisfaction facets as noted in Tables 2.1 and 2.2 where operationalizations of these facets may be found. At times, the facets included in the proposed framework are more general,

Table 2.3: Facets of job satisfaction framework for Operations Management

| Facet of job satisfaction | Definition | Operationalization sources | Linking OM operationalization variable |
|---|---|---|---|
| *1. Task content related* | | | |
| 1.1 Task variety | The extent to which the job requires workers to perform a range of tasks on a job | Self-reported likert scales, A2, B19, D4 | Number of dissimilar tasks |
| 1.2 Task identity | The extent to which a job involves a whole piece of work that can be easily identifed | Self-reported likert scales, A2, D6 | Proportion of occasions in which order pickers are allowed to complete a pick in a bucket brigade or any other work sharing schemes |
| 1.3 Autonomy | The extent to which a job allows freedom to workers on how to execute their job -method-, when to perform each task -schedule- and react to unexpected circumstances -decisions-) | Self-reported likert scales, A4, B10, C5, D1, D2, D3 | Number of options a worker can choose from in a schedule |
| 1.4 Feedback from the job | The worker is provided with feedback related to his performance at the job by automatic means | Self-reported likert scales, D7 | Frequency of feedback provided by automatic systems Variability of upstream/downstream queues |
| 1.5 Task meaningfulness in relation to others | The perceived impact the task has on their peer's work and customers | Self-reported likert scales, A3, C4 | Probability that downstream worker colleague is starved of work |
| *2. Social interactions related* | | | |
| 2.1 Opportunity for social interactions | The degree to which the job offers opportunities for workers to interact | Self-reported likert scales, A6, C19, D17 | Average percentage of time allowed to interact with peers |
| 2.2 Fairness in compensation and work-load distribution among workers | The degree to which the workers feel compensated for their work and have equal treatment | Self-reported likert scales, B7, C13, D20 | Standard deviation in work load distribution among workers |
| 2.3 Job appraisal and feedback provided | The degree to which feedback is provided by the workers' peers and supervisor | Self-reported likert scales, A5, B8, B12, B17, B18, C18, C19, C20 | Frequency of feedback provided by super |
| *3. Physical and organizational environment related* | | | |
| 3.1 Exposure to fatigue, discomfort and health risks caused by the physical environment | The extent to which individuals are subject to fatigue, health risks due to plant and work station layout | Fatigue measured by oxygen volume intake or maximum holding time<br>Discomfort measured in Borg's (1981) scale | Percentage of time workers are in awkward/stressful positions, weighed by severity |
| 3.2 Exposure to fatigue, discomfort and health risks caused by the organizational environment | The extent to which individuals are subject to fatigue, health risks due to schedules and work intensity | Health risks measured as expected number of days due to temporal incapacitation per man-year<br>Self-reported likert scales, B6, B20, C1, C9, C24, C25, C26, C28, C29, D8, D18, D19, D20 | Time spent working continuously Percentage of time allowed for rest Number of cycles completed per unit of time |
| 3.3 Work/leisure balance | The extent to which the job provides free time, opportunities for leisure, beyond the minimum requirements by law | Self-reported likert scales, B6, C1, C14 | Quality weighed number of continuously hours/days available for leisure |

than the facets included in previous frameworks. This is the case, for example, with "Exposure to fatigue, discomfort and health risks (organizational factors)" where all organizational factors with an effect on fatigue, discomfort and health risks are included (see Table 2.3). In this way, specific physical facets from the Work Compatibility Model are included (i.e. adequacy of sensory design (C24), strength (C25), endurance (C26), upper and lower body posture(C28-C29)). At the same time, given the need for a link with operations management variables, Table 2.3 also provides an example of a linking variable for each job satisfaction facet to operations management decision variables. These linking variables are equivalent to the individual exposure variables defined in our framework (see Figure 2.1).

Once a relevant facet of job satisfaction and an operations management linking variable are identified, the modeler must consider how to include such linking variables in the objective of a decision model. Take for example, the case of task variety as a facet of job satisfaction. It is not necessarily true that designing a job with a large number of tasks will result in a higher level of job satisfaction. Indeed, given the skill capacity of the worker and his own preferences, it is possible that instead there is a specific and desired number of different tasks to aim for; implying that there is a concave relationship between the linking variable and the worker's job satisfaction as observed within a particular facet. Hence, we recommend the following approach to formulate the objective of an operations management decision model including job satisfaction facets:

**Modeling recommendation 11** *To include a linking variable as a proxy for a job satisfaction facet in an operational model, one should first consider whether the desired objective is a maximization of the facet or a minimization of the discrepancy between the job satisfaction facet level and a desired level.*

## 2.5 Modeling human factors in operations management

This section does not intend to provide a comprehensive overview of all operations management decision models that may have an impact on either a workers' individual performance or a particular facet of their job satisfaction. This section, instead, has the purpose of the applicability of our performance and job satisfaction frameworks for modeling; providing directions on how knowledge of worker behavior can be incorporated into operations management decision models. We identify four categories of operations management decision models whose decisions are the most likely to affect worker performance or job satisfaction: 1) Scheduling and timetabling; 2) Workflow design models; 3) Job appraisal and incentive design models; 4) Layout design models. Note that the third area is not a traditional operations management decision model area. This area is more commonly associated with labor economics. However, in view of the important operational impact and distinct influence of these decisions in specific operational settings, we argue for its inclusion in our review of operations management models. Furthermore, note that the first three decision models concern the organizational environment of a productive system, whereas the last concerns the physical environment.

In Tables 2.4, 2.5, 2.6 and 2.7 we illustrate how relevant operations management variables in existing operations management decision models affect factors either driving individual performance or contributing to job satisfaction. Moreover, we use these tables to identify research opportunities stemming from existing work. Such research opportunities may include the need for further modeling to incorporate human related aspects into existing models or for more empirical work that can be used as a foundation for future operations models where worker–specific factors are important.

### 2.5.1 Scheduling and timetabling

The literature on scheduling and timetabling is extensive (see (Pinedo, 2008) and Ernst et al. (2004) for a comprehensive review on workforce scheduling). Scheduling and timetabling are arguably the operations management decision processes with the most direct influence on worker' well-being and performance because the assignment of workers to shifts, tasks, work/rest and vacation periods are explicit decision variables.

At the tactical planning level, the assignment of vacation periods and shifts to workers, dependent on worker demands, are typically driven by minimum staffing levels, legal constraints and firm policies. A few cases exist where worker related well-being measures have been explicitly included in shift models. One such model is that of Kostreva et al. (2002) in which the quality of a schedule in terms of endurance was measured as the deviance from naturally occurring circadian rhythms. However, the drawback of such a model is that it considers circadian rhythms as the only fatigue related factor. Broader approaches are also available, including that of Chen and Yeung (1992). They developed a goal programming model for nurse scheduling that includes, as objectives, the minimization of the number of rotations directed backwards (known to disrupt circadian rhythms) and the minimization of the maximum consecutive work periods. These additional objective terms serve as proxies for minimizing fatigue and impaired performance. Similarly, Malladi and Min (2004) used Analytic Hierarchy Process (AHP) to assign weights in balancing economic and ergonomic cost objectives. However, all of these approaches rely on integrating methods that are not based on actual empirical data and thus reflect the fragmented literature on incorporating scheduling factors that relate to fatigue and risk for accidents.

Another approach for vacation assignment, attempted by Chong and Stervell (1985) has been to allow workers the autonomy to bid on their vacation periods thus revealing their preferences. However, this approach is cumbersome to implement, may not necessarily reveal the workers' true preferences and may result in gaming behavior that leads to a misalignment with safety goals or long term job satisfaction (e.g. some workers may be willing to temporarily experience burn-out). Still, an opportunity exists for a more integrated approach by using meta-analytic studies, such as the one by Spenser et al. (2006) that do quantify the relative impact on fatigue and accidentability; these studies are described in Section 2.3.1.

It is important to note that more empirical work is required for quantifying the fatigue and accidentability effects of shift scheduling. In particular, quantifying the differentiated value of free days may be interesting as it is plausible to assume that days-off in summer periods or school vacation periods may be socially more valuable for workers and thus should be weighted as more important in an objective to create value. Furthermore, it is important to note that effects of different schedules on work performance still need to be addressed empirically. Specifically, the fact that worker related effects occur over longer horizons of time implies challenges in data collection and analysis of such empirical notes. Hence, we make the following recommendation for empirical researchers:

**Empirical recommendation 8** *For empirical research, long-term (i.e. weeks and months) longitudinal studies are required to establish long-term links between scheduling practices and operational performance along with job satisfaction measures.*

At the operational level, where workers may be assigned to multiple tasks (i.e. job rotation models) or breaks are assigned, research opportunities also exist. An overview of such opportunities is given in Lodree et al. (2009) along with a framework to incorporate them. In particular, Lodree et al. (2009) propose the use of existing sequence-dependent task processing time models that also allow for the modeling of improving processes, due to increased learning and motivation, and degrading processes, due to increased levels of fatigue and discomfort. Moreover, they propose the use of rate modifying activities (i.e. activities that if introduced may enhance the productivity of later activities) to model the effect of resting periods or periods in which a different task is performed (work rotation models) allowing the physical recovery of specific body parts. The advantage of this approach is that the structure of the model is independent of the exact functional form of performance improvement and deterioration. This certainly provides a useful strategy for dealing with unconfirmed functional forms that relate fatigue, discomfort and learning to individual performance:

**Modeling recommendation 12** *In modeling unconfirmed functional forms from the behavioral/ergonomics literature, we recommend decoupling the structure of the model from specific empirical functional forms so that new discoveries of these forms may be easily adopted.*

In addition, work-rest models may also make use of Bechtold et al.'s (1984) modeling approach. However, as noted earlier, the empirical basis needs to be further validated because increased fatigue does not necessarily result in a decrease in performance. An alternative approach for work-rest models will be to use Konz's (1998) guidelines where the emphasis is on safety and avoidance of unduly fatigue instead of the effects on individual performance.

Table 2.4 provides an overview for of the opportunities due to the incorporation of worker-specific factors in scheduling models.

### 2.5.2 Workflow design

Workflow design refers to operations management models that address the flow of work between individual work places and may include queuing and simulation models. These models also present an important opportunity for incorporating worker-related human factors. Given the advances in empirical work describing the motivational effects on performance of productive systems, including the role of peer pressure, work pressure and goal setting in operational contexts (as seen in Section 2.3.1), workflow design is a promising area for modeling operational decisions that affect individual performance and productive system performance.

Table 2.4: Research opportunities for worker-related scheduling models

| | | Individual performance factor | | | |
|---|---|---|---|---|---|
| Operational Model Category | Decision and/or exposure variable | Perceived benefit of work | Perceived cost of work | Job satisfaction | Work done & work remaining |
| *1. Vacation planning*<br>Classic objectives:<br>Minimize workforce related costs<br>Maximize coverage of workforce demands | Starting/finishing date of vacation period<br>Duration of vacation period<br>Variation of duration of vacation periods and preference between workers involved in model | Intrinsic desirability of performing the job may be affected | Fatigue:<br>Is leisure time enough for recovering? | Work/life balance being able to interact with family and friends (3.3)<br>Equitable treatment in vacation assignment (2.2) | Bidding scheduling systems have been proposed and implemented by Chong and Strevell (1985).<br>Schedule models that consider the value of different vacation periods based on empirical studies are still needed. |
| *2. Shift scheduling*<br>Classic objectives:<br>Minimize workforce related costs<br>Maximize coverage of workforce demands | Shift type (morning/evening/night)<br>Shift rotation<br>Starting time<br>Shift duration | Intrinsic desirability of performing the job may be affected | Fatigue:<br>Sleepiness, circadian rhythm | Endurance (physical and mental) and accidentability risk (3.1)<br>Equitable treatment in the work-comparison (2.2) | Multi-criteria decision models exist that consider different factors that affect accidentability and fatigue (e.g. Chen and Yeung, 1992).<br>A more integrated approach is still required that weighs these factors based on empirical evidence. |
| *3. Job rotation scheduling*<br>Classic objectives:<br>Maximize coverage of workforce demands<br>Minimize lateness/tardiness | Task sequence | Intrinsic desirability of performing the job may be affected | Skill:<br>Learning/ forgetting processes | Task variety according to assignments (1.1) | Lodree et al. (2009) suggests the use of sequence dependent task and rate modifying activities for incorporating learning and forgetting processes.<br>Models incorporating the adequacy of task variety are still required. |
| *4. Work-rest (break) scheduling*<br>Classic objectives:<br>Maximize production output | Work period/rest period assignment<br>Shift duration | Rest:<br>Increase in maximum productive capacity | Fatigue:<br>Deterioration of maximum productive capacity | Endurance (physical and mental) and accidentability risk (3.1) | Bechtold (1994) proposes work-rest models that assume linear and exponential deterioration and recovery of productivity.<br>More empirical work is required to determine real deterioration and recovery of production due to work and rest periods. Models may also include intensity of work as a factor affecting resting length. |

Suri and Treville (1986) already made an attempt by modeling a simplified Just-In-Time production line with two servers. They used a queuing model to incorporate acceleration effects of a worker in order to avoid starvation and/or blockage of a server; thus, obtaining an optimal level of Kanban cards or work-in-progress in the system. Based on empirical data from previous experiments in Schultz et al. (1998) and Schultz et al. (1999), Powell and Schultz (2004) propose Markov simulation models of a production system to show that workers who tend to speed up or slow down may increase the overall efficiency of a production system in which feedback is enhanced due to fixed buffer sizes. Moreover, contrary to state-independent worker behavior where larger line lengths (i.e. a larger number of stations) decrease performance (Conway et al., 1988), larger state-dependent production lines may actually increase efficiency. In this way, it is shown that by incorporating realistic human behavior into production performance can actually alter decisions to be made (in this case, line length). Finally, Schultz et al. (2010) provide a quadratic programming model for assigning workers in a serial-line given the skill level of a worker and his sensitivity to the work pace of his peers based on findings of a previous empirical study with archived data.

Potential research questions remain, including how to set the batch sizes that maximize throughput given that workers may be assigned goals to perform quickly while learning effects may also be at play (Schultz et al., 2003). Other workflow design parameters may include job rotation strategies within production lines for trading-off task variety (a facet of job satisfaction) and flexibility with line throughput. Shared work stations can also be studied in specific application areas such as in the case of "pick and pass" order picking systems in distribution centers (Tompkins et al., 2003), where there may be more workers than stations and protocols need to be devised to assign workers to work stations depending on their availability and warehouse demand. In addition, self-organizing schemes, such as the one proposed by Bartholdi and Eisenstein (1996), that are proven to balance themselves in the presence of disturbances, may be analyzed in conjunction with regression towards the mean dynamics, in which workers attempt to match the work pace of their peers (Schultz et al., 2010), to test if the rate of convergence to balancing states increases.

Moreover, we emphasize the need for more empirical investigations of long term effects of social cohesiveness, work pressure (chronic fatigue) and job satisfaction effects in relation to operational variables (e.g., low inventory, work-line assignment, manufacturing cell assignment among others). This also prompts us to remark on possible research approaches in dealing with these long term effects:

**Modeling recommendation 13** *In modeling long-term job satisfaction related effects, observable proxies in the short-term such as discomfort ratings or social interaction frequency may be included as objectives while a link between the short-term proxies, and the long-term desired effects (facets) of job satisfaction and the overall impact on job satisfaction) may be found in existing literature and are subject to further empirical work.*

Perhaps a new dimension to be explored in human workflow design is the derivation of dynamic control protocols of workflow. For instance, instead of constraining buffer sizes to fixed values, allowing them to vary according to the individual responsiveness of a worker, may provide the possibility of reaping additional motivation form the worker when it necessary to accelerate production. It is important to note here that part of the research required to implement this involves devising procedures for obtaining on-line characteristics for individual workers including responsiveness to peers, learning rates and forgetting rates. Hence, for empirical researchers, the following recommendation is made:

**Empirical recommendation 9** *Empirical research can be combined with modeling research to test on-line, dynamic models of performance where operational variables that affect responsiveness to peers, learning and forgetting may be adjusted over time.*

A promising tool for modeling all these complex interrelationships in work flow models is that of systems dynamic models. Already, (Oliva and Sterman, 2001) has used this technique for illustrating trade-offs between work performance pressure and quality, validating this with the use of field-data.

Table 2.5 provides an overview for opportunities to incorporate worker-specific factors in work-flow models.

### 2.5.3 Goals, incentives and job appraisal design

Although not a classic area of operations management modeling, incentive and job appraisal design are promising areas for future decision modeling. Although incentive design for workers has usually been studied in the field of economics, incorporating the particular characteristics of operational contexts may be useful. For example, Siemsen et al. (2007) develop a game theoretical two-agent, two-task model, with supporting empirical evidence, that shows the added value of distinguishing between different operations management (work-related) links when devising optimal incentive schemes rewarding/penalizing individual or group performance. Specifically, Siemsen et al. (2007) distinguish between 1) the production of one worker affecting that of another worker, 2) the worker spending effort to help another worker and 3) workers sharing job-related knowledge.

Research questions like whether to have rewards for group or individual outcomes, how to set goals (individually and in a group), how frequent feedback should be given and how to combine incentives and goals, still remain unresolved despite all the available interest in this area from economics and the behavioral sciences. All of these research questions also involve detecting behavioral patterns of workers to optimize individual goal levels, monetary incentives and frequency of feedback. However, this personalized approach requires a balance with goal alignment considerations (economic design) as well as long-term effects due to fairness considerations and social cohesiveness (important facets of job satisfaction).

Table 2.5: Research opportunities for worker-related work-flow models

| | | Individual performance factor | | | |
|---|---|---|---|---|---|
| Operational Model Category | Decision and/or exposure variable | Perceived benefit of work | Perceived cost of work | Job satisfaction | Work done & work remaining |
| *1. Blocking rules in production lines - control of work in progress in production lines*<br>Classic objectives:<br>Maximizing throughput<br>Minimizing makespan | Average and standard deviation of queue length | Peer incentive:<br>Avoiding peers being idle | | Perceived task meaningfulness in relation to others (1.5) | Powell and Schultz (2004) tested blocking rules and propose a model that takes into account workers accelerating when feedback is more salient. More empirical work is required for evaluating the desirability of such policies from a job satisfaction point of view. |
| *2. Assignment of worker to workplace*<br>Classic objectives:<br>Maximize line efficiency<br>Minimize staffing costs | Worker position in a production line | Peer incentive:<br>Avoiding peers being idle | Work pressure:<br>Arrival rate of jobs. | Task variety according to assignments (1.1) | Shultz et al. (2010) propose a model to assign workers in an assembly line based on empirical data.<br>Inclusion of task variety fit as an objective could be a potential line of research. Other contexts such as cell manufacturing could be studied. |
| *3. Work sharing policies*<br>Classic objectives:<br>Maximize throughput in production lines | Protocols for sharing work (i.e. Decision rules for allocating workers to shared workstations) | Peer incentive:<br>Worker equity, work pressure | | Task identity:<br>Has the worker the opportunity to finish a recognizable piece of work? (1.2) | There is work regarding personality differences and the effect on work sharing environments (Juran, 1997).<br>However, it is important to study empirically the satisfaction of workers with these policies. |
| *4. Batch sizes*<br>Classic objectives:<br>Minimize makespan<br>Minimize backlog | Batch size<br>Goals & deadlines for executing batch | | Skill:<br>Learning/ forgetting processes, attention and goal-focus | Task identity:<br>Has the worker the opportunity to finish a recognizable piece of work? (1.2) | How to breakdown production demand into batches and assign goals in the shop floor for operational and job satisfaction objectives are research questions yet to be answered. |

Furthermore, all of these questions may be asked in combination with other decisions including scheduling decisions and workflow decisions. For example, in scheduling with variable demand, goals and incentives may aid as a temporary source of extra capacity without requiring extra hours or extra personnel. Moreover, in production lines temporary motivational leverages, in terms of goal setting or additional monetary incentives, may be used to solve issues with bottleneck resources.

Table 2.6 provides an overview of the opportunities to incorporate worker-specific factors in terms of incentives, goal-setting and job appraisal within operations management models.

### 2.5.4 Layout design

The literature on layout design for facilities is extensive, Meller and Gau (1996), and more recently, Singh and Sharna (2006) provide an overview of the field. Although it is true that layout models already incorporate human factors by considering area requirements for workers to perform their work with a reasonable degree of comfort, there is space for more explicit worker-related aspects in layout design. In designing the shape of a production line, feedback effects may be a relevant factor. For example, U-shaped designs allow workers to have an overall view of the operations and thus may anticipate high or low periods of workload. Furthermore, learning rates may be enhanced by designing layouts that enable workers to observe their colleagues and in particular "role" models (i.e. exemplary and experienced workers) that may act as "teachers".

Table 2.6: Research opportunities for job appraisal and incentives design

| | | Individual performance factor | | | |
|---|---|---|---|---|---|
| Operational Model Category | Decision and/or exposure variable | Perceived benefit of work | Perceived cost of work | Job satisfaction | Work done & work remaining |
| *1. Goal assigned*<br>Classic objectives:<br>Maximize performance<br>Minimize variability of performance across workers<br>Minimize response times | Type of goal: Productivity, quality or both<br>Goal level and deadline<br>Goal scope:<br>Individual/group goal<br>Goal based incentive for motivation and focus | Fatigue:<br>Higher work intensity may increase fatigue<br>Distraction:<br>Other performance dimensions not included in goals are perceived as less valuable | Autonomy may be affected depending if the goal is assigned rather than self-assigned (1.3) | | An integrated approach is required in this area. Empirical results exists about the properties of each type of motivational enhances (goals,incentives) but more research on the operational context is needed to develop further models.<br>Further principal-agent models (see Siemsen et al., 2007) may be made for modeling the alignment of supervisor - worker goals when goals, incentives and feedback is given. System-dynamic models (Olvia and Sterman, 2001) may shed light on how feedback, incentives and performance dimensions may interact over time. |
| *2. Incentive schemes*<br>Maximize performance<br>Minimize variability of performance across workers | Piece-rate (level)<br>Bonus contingent on goal accomplishment | Direct incentives for enhancing motivation | Possible enhanced awareness on the effort required to perform the job | Fairness in compensation may be affected (2.2) | |
| *3. Feedback*<br>Maximize performance<br>Minimize variability of performance across workers<br>Minimize response times | Frequency of feedback<br><br>Salience & hierarchy of multiple goals (productivity, quality) | Awareness of progress and thus and incentive for reaching the goal | Possible enhanced awareness on the effort required to perform the job | Feedback in itself is a facet of job satisfaction, a lack of it is considered undesirable (2.3)<br>Highly frequent feedback may affect perceived autonomy (1.3) | |

Further, in warehouse layouts the arrangement of picking areas may also affect aspects of job satisfaction. Although models exist for estimating congestion probabilities (two pickers meeting in an aisle), which can lower picking throughput due to blockage, a low degree of congestion may be beneficial as they may enhance a facet of job satisfaction: adequate interaction with co-workers. Picking on large floor spaces with very few encounters may be undesirable from a job satisfaction point of view as well as motivational point of view of performance (i.e. the element of peer pressure is non-existent).

At a more detailed level, slotting decisions regarding where to locate products in warehouses have received attention due to their impact on discomfort in scenario based studies (Saccomano, 1996 and Jones and Battieste, 2004 and Petersen et al., 2005). In Chapter 5, we use field data that is able to trade-off an economic objective (i.e. throughput of a picking system) with a proxy for a facet of job satisfaction (i.e. discomfort).

Table 2.7 provides an overview for opportunities to incorporate in operations management models worker-specific factors related to layout design.

## 2.6 Conclusions

In this paper we showed that classical operations management objectives should be expanded to include facets of job satisfaction as perceived by the workers involved in the operations. By taking a decision driven perspective, we have shown that existing knowledge regarding the behavior of workers may be useful when incorporated in operations management decision models. The usefulness is specifically shown in cases where the influence of operational variables would either affect operational performance or job satisfaction.

Table 2.7: Research opportunities for layout models

| | | Individual performance factor | | | |
|---|---|---|---|---|---|
| Operational Model Category | Decision and/or exposure variable | Perceived benefit of work | Perceived cost of work | Job satisfaction | Work done & work remaining |
| *1. Production line shape*<br>Classic objectives:<br>Minimization of expect travel distances | Layout shape type (e.g. I, L, S, U)<br>Workstation location pair | Peer incentive:<br>Adjustment of work pace to the performance of others<br>Anticipation to "heavy workload" may affect work rates | Skill:<br>Opportunities for faster learning based on peers example | Task meaningfulness:<br>Perceived degree of team interdependency at work (1.5) | More empirical work is required regarding the effects of learning form others and the impact of job satisfaction. Layout models could incorporate such insights. |
| *2. Warehouse layout design (and routing)*<br>Classic objectives:<br>Minimization of expect travel distances and/or picking cycles | Probability of meeting /congestion | Intrinsic desirability of performing the job may be affected | | The opportunity for social interactions may be affected (2.1) | Existing models for estimating congestion (Gue et al., 2006) may be used to estimate the probability of social encounter as job satisfaction facet criterion to be maximized. |
| 3. Storage assignment models<br>Classic objectives:<br>Minimization of expect travel distances and/or picking cycles | SKU-location pair | | Fatigue:<br>Higher work intensity may increase fatigue | Discomfort due to upper and lower body posture (3.1) | Initial empirical work exist (see Chapter 5 of this thesis) and find partial alignment of operational and job satisfaction related objectives. |

Our objective was to integrate the diverse bodies of knowledge of worker related factors to gain insights for operations management models that involve worker-specific factors. To achieve this objective we first proposed the general framework depicted in Figure 2.1, then a framework for linking worker related factors and individual performance in Figure 2.2, and finally a framework detailing the relevant facets of job satisfaction for operations management as shown in Table 2.3. Tables 2.4, 2.5, 2.6 and 2.7 then illustrated the application of these frameworks to current or potential operations management models.

Our decision-making approach provided a focus to our literature review of worker related factors by limiting it to cases where operations management variables may induce an observable change in human factors that affect individual performance or job satisfaction. This approach was also useful for identifying the limitations of current knowledge. Based on the opportunities and limitations, we provided recommendations for the operations modeler on how to include specific worker relation factors in operations models. These limitations were also indicated as opportunities for further empirical research to increase the understanding of how worker related factors are linked to performance and job satisfaction.

In particular, we showed that certain worker–specific factors that affect performance, including, learning, forgetting, goal setting and peer pressure have currently a thorough theoretical underpinning and their link with performance can be described mathematically (albeit in a limited way) for operations management modeling. Other worker-specific factors that affect performance, including incentives, fatigue, feedback and effort evaluations by workers, have relationships with performance that are less understood and that are not described to a sufficient level of detail that grants a proper mathematical characterization of the relationships. In addition, we found that there is variety in the recognized facets of job satisfaction by different models of job satisfaction. We found that the links of job satisfaction facets to operational variables require more exploration. We also proposed the use of established short-term proxies for long-term effects as a means to address limitations in linking specific job satisfaction facets with performance. Importantly, we proposed work incentive and appraisal design as a new area of research that not only belongs to the labour economic field, but should also be studied by operations management scientists.

In summary, for a future research agenda,we propose a two-fold approach: 1) Conduct empirical work that may establish key links required for decision-making modeling purposes; 2) Develop models that are premised on solid empirical evidence. Performing both research activities in parallel will enable the study of Behavioral Operations for Workers to grow within the general area of Behavioral Operations and the larger field of Operations Management.

# Chapter 3

# Behavioral goal setting models for operations management: A theoretical approach

## 3.1 Introduction

Operations management models often assume implicitly that people are predictable, stationary and emotionless, unaffected by external factors (Boudreau et al., 2003). These are assumptions are justified if no interaction exists between the decision variables of the model and factors that pertain to the workers' performance. If goals are assigned in production contexts, and an operations management model attempts to model the assignment of goals, then assuming that workers are predictable, stationary and emotionless, unaffected by external factors may be unjustified. Instead, an operations management model that attempts to model the assignment of goals should draw from the theory that identifies and explains the effect of setting concrete, specific goals on individuals and groups (Locke and Latham, 1990): Goal Setting Theory. The main result of Goal Setting Theory is that setting sufficiently challenging and specific goals boosts performance. In fact, a meta-analysis of 239 laboratory and 156 field studies demonstrates that setting challenging and specific goals results in a significantly increased performance when compared to "do your best strategies" with an increase of mean to standard deviation ratio ranging between $d = 0.48$ and $d = 0.80$.

These findings imply that an external factor (i.e. the goal) *has* an effect on work performance and work processing rates. Despite the potentially significant impact of these findings on operations management, to the best of our knowledge, there are only few studies on goal setting from the operations management point of view. This is study is done by Doerr (1996) where the convenience of individual and group goals are studied in a production line setting. Similarly, van Mierlo and Kleingeld (2010) analyzed the convenience of setting individual and cooperative goals in settings where interdependence among workers exist. Also in an operations management context, a thesis by Vijfeijken (2004) looked at the problem of designing a goal and reward system for work that is interdependent, however his work did not consider actual workflow considerations. Furthermore, indirect references to goal setting theory appear in OM studies that address the influence of workload on performance (Schultz et al.(1998), Gutierrez and Kouvelis (1991) and Bendoly and Prietula (2008)). A study by Schultz et al. (2010) also linked goal setting theory with the goal of avoiding starvation of co-workers in a production line.

Operations management, on the other hand, has a strong focus on the analysis of the time dimension. Models concerned with throughput, response time and makespan are evidence of this. In the field of OM not only is performance important but performance over time as work requirements themselves vary over time. Quantitative production goals in operational settings also include deadlines and variations in performance over time. This contrasts with Goal Setting Theory, which has been criticized for being static (Latham, 2007). In Goal Setting Theory, total performance at the end of a period is the main variable to be explained. Hence, for adapting Goal Setting Theory to operations management, the time dimension remains to be explicitly incorporated.

In this chapter, we review Goal Setting Theory's main finding and extend it for use in operational contexts such as manufacturing and distribution, where workers are assigned a quantitative goal in terms of items or orders to be accomplished within a given time period. The knowledge from goal setting articles is typically not available in a format that is sufficiently mathematical to be used in quantitative OM models. This is actually a problem that arises for many more situations in which one would like to include worker specific factors in OM models (see Chapter 2) of this thesis and Boudreau, 2003).

Our study therefore starts by specifying the goal difficulty–performance relationship in mathematical language. However, our main contribution is to study the process that leads to such performance that has not previously been studied. In particular, we ask: How do workers regulate their work pace under the influence of goals? Answering this question could be informative for re-developing OM work flow models that typically assume stationary behavior and do not include varying goals as an external variable. Additional insights may provide additional information for OM models of productive systems such as queuing and simulation models. Moreover, the identification of common patterns regarding how workers regulate their work pace can also be used as a reference when monitoring the process followed by workers to achieve production goals. Finally, if patterns are identified in work regulation given varying difficulty of goals assigned, such patterns may be helpful in assessing whether an assigned goal effectively increases individual performance to the maximum.

This chapter takes the implementation of incorporating worker specific factors in OM models further than Chapter 2 by formally characterizing the relationships involved in decision making models. From the models, we derive alternative propositions and contrast these with the existing literature. This allows us to subsequently test these propositions empirically at a later stage in an experimental study reported in Chapter 4. By doing so, we are then able to obtain insights for operations management that are grounded in theory and buttressed by empirical evidence.

We model the worker as a decision maker who attempts to maximize his desirability (translated in economic terms to utility) for working at a certain work pace, acknowledging that motivation is the antecedent of action. This approach is in-line with the tradition of Behavioral Economics and more recently, Behavioral Operations (Gino and Pisano, 2008) where utility models that are based on empirical findings are used for predicting actual choices. Note that utility functions can be modified to reflect particular characteristics of the way individuals make decisions (Tversky and Kahneman, 1992). We propose two alternative models, based on alternative views from the industrial psychology literature, that conjecture two different ways by which workers maximize their satisfaction. In the first model we assume that the worker is myopic considering only his satisfaction on the "spot", while in the second model we assume the worker is a planner who considers his satisfaction for the whole time period. These models are all based on basic assumptions that are grounded in the literature.

Wu et al. (2004) also present a decision model that attempts to describe the effect of goals on work pace. However, our work differs fundamentally from their model in our application to OM contexts. Wu et al. (2004) consider individuals with the different decision problem of persisting or not towards the goal. This is common in contexts like sports where sportsmen may decide to continue or not executing an exercise such as push-ups. However, for regular routine work where workers do their tasks for a pre-specified period (e.g. shifts or time blocks)the situation is different. Instead of deciding whether to persist or not in executing the job, workers decide on the amount of effort put in executing the job and thus the work pace at which they execute it. That is, if the goal is production related. Our models then contribute by taking into account time as a critical dimension in OM contexts, allowing the work pace to vary over time in dynamic decision models. Moreover, we introduce the concept of combining intrinsic (normal work pace rhythm driven) and extrinsic (goal oriented) motivational sources.

The rest of this chapter is structured as follows. In Section 3.2 we provide a short literature review on the goal difficulty-performance relation and what is known about work pace regulation while identifying specific research questions that remain to be unanswered. Next, in Section 3.3, we specify the scope and operational contexts where these research questions are applicable. Section 3.4 presents the underlying assumptions of our models supported by findings in the literature and proposes utility functions for modeling sources of motivation. In Section 3.5, we develop a decision making model from a myopic model and from it derive testable hypotheses for Chapter 4. Similarly, in Section 3.6, we develop a decision making model from a planner model and from it derive testable hypotheses for Chapter 4. Finally, in Section 3.7, we provide a general discussion of the hypotheses generated and some concluding remarks.

## 3.2 Literature review and research questions

Originally, Goal Setting Theory posited a linear relationship between goal difficulty (or goal level) and performance (Locke, 1968). However, this initial proposition has eveolved in time. First, Locke and Latham (1982) report that the linear relationship tends to level off when workers reach the limit of their ability. Second, Erez and Zidon (1984) report an increase in performance followed by a drop in performance. The inflection point shown in their experiment is at the point where approximately only 10% of the subjects are able to achieve the goal. Erez and Zidon (1984) argue that this occurs because of a lack of goal commitment. An argument made by observing a correlation between the lack of commitment and drop in performance. Nonetheless, See et al. (2006), argue that even in the presence of goal commitment, performance may deteriorate because exceedingly challenging goals are perceived as distant.

Besides differences in reports in the precise description of the difficulty–performance relationship, it must also be noted that most of these studies were applied in contexts different than the operational contexts under analysis here (for a review see Locke and Latham (1990)). Goal setting studies that analyzed the goal difficulty–performance relationship typically required subjects to stop working once they reached the goal, not allowing for exceeding the goal (Locke and Latham, 1990; See et al., 2006). However, in factories, service centers and distribution centers, workers usually work for *fixed* time periods instead of variable periods depending on when an assigned quantity of jobs has been processed. For this reason, it is still worth confirming the existence of the linear goal difficulty-performance relationship for OM contexts. Hence, in this chapter we ask:

**Question 1** *What are the effects on individual performance (i.e. cumulative performance of an individual measured at the end of the assigned period) if the goal difficulty (level) increases?*

Furthermore, Locke (1965) reports an interaction between ability and goal sensitivity, where performance tends to level–off earlier for less skilled individuals and thus low-level individuals tend to be less sensitive to goal difficulty. However, Crawford et al. (1983) find the opposite result, where low performers improved more in their performance than high performers. Locke and Latham (1990) argue that this apparent contradiction may be solved with the possibility of a ceiling effect where high performers are already working to the best of their ability. At the same time, in productive systems, workers with different skill levels (i.e. maximum level of performance) exist, workers are not homogeneous in their skill levels. This means that for contexts in operations management, it is important to study the effect of varying skills on total performance, in conjunction with goals. Thus, we ask for main and interaction effects with goal difficulty and varying skill levels on performance:

**Question 2** *What are the effects on individual performance of increasing skill level under the influence of a goal?*
**Question 3** *What are the interaction effects of increasing goal difficulty (level) and skill level on individual performance?*

By contrast, in the literature, the effect of goals at the work pace regulation level has received significantly less attention than the goal difficulty-performance relationship. In this respect, the goal–gradient hypothesis (Hull, 1965) is one of the earliest propositions on how individuals regulate their progress towards the goal. The goal–gradient hypothesis posits that individuals tend to accelerate their progress the closer they are to attaining the goal. Recently, the hypothesis has been replicated in the sports context with a running task (See et al., 2006) and in the marketing context (Kivetz et al., 2006) where customers are observed to purchase more frequently when they get closer to a certain consumption goal with a certain reward such as a free cup of coffee.

The goal–gradient hypothesis appears to be related to the phenomenon of procrastination that consists of individuals exerting more effort towards the deadline (Ariely and Weertenbroch, 2002). Several explanations have been given for this phenomenon including the discounting of future benefits such as a narrow focus on the present (Buehler et al., 1994) and an underestimation of past experiences in terms of task durations (Roy et al., 2005). However, in all of these studies no distinction was made between the goal and the deadline as the goal was supposed to be achieved at the deadline. This is unlike the operational context that we analyze here where the goal can be achieved *before* the deadline and not later. Hence, it is not clear from all these studies whether the acceleration was towards the *assigned goal* or towards the *deadline*, when this distinction is relevant.

**Question 4** *How is the work pace regulated under the influence of a given goal and deadline?*

In addition, there is a report from the literature that goals and deadlines (Bryan and Locke, 1967) affect an individual's regulation of work pace such that they actively adjust their work pace (by accelerating or decelerating) to achieve the assigned goal by the deadline. Bryan and Locke (1967) argue that their observation is a generalization of Parkinson's Law (1962) which states that work tends to expand to fill the time available for its completion. The generalization considers that work not only expands, but also contracts if it needed to fulfill the goal within the assigned deadline. A similar idea is posited by Carver and Shreier (1998) who view the goal and the deadline as inputs to set a reference value for work pace in a closed feedback loop system whose purpose is to minimize the discrepancy between the *actual* work pace and the *reference* work pace. Thus, for the case of work pace regulation, we study the effect of varying goals on work pace regulation as follows:

**Question 5** *What are the effects on work pace regulation if the goal difficulty (level) is increased?*

Finally, just as skill levels may affect the goal difficulty–performance relationship, we also study how it affects the work pace regulation of workers in conjunction with the influence of goals. Therefore, we ask the following questions regarding main and interaction effects of skill levels on work pace regulation:

**Question 6** *What are the effects on work pace regulation if the skill level is increased under the influence of an assigned goal and deadline?*
**Question 7** *What are the effects on work pace regulation when the skill level and assigned goal interact?*

## 3.3 Scope and approach

The goal-setting case which we address in this chapter involves an externally set deadline $D \in \mathbb{R}^+$ (fixed time horizon), as well as an externally set goal $G \in \mathbb{R}^+$ stated in terms of the number of units processed in a production environment or the number of picks in a distribution environment. We assume that it is understood in the firm, that the worker ought to achieve and, if possible, over-achieve the goal set by the management. Despite the fact that we consider no monetary rewards or punishments for over-achieving or underachieving the goal, the goal serves as a way to evaluate the workers' performance by the managers and by the workers themselves. Furthermore, it is also implicitly assumed that work-related benefits may be obtained by repeatedly achieving or over-achieving the goals including promotions and salary increases. In practice, it is important to note here that in the US, goals are often linked to increased pay within piece-rate schemes; in the European Union, piece-rate schemes are not allowed and thus, goals are more often related to long-term benefits.

We assume that the deadlines are short-term (e.g. within a 4 hour block of a working shift), that the work is uninterrupted and that the cycle time for producing or processing each item is short (say under 10 minutes). The job should be such that the worker can perceive a clear deterministic-like relationship between his exerted effort and his work performance. Hence, we limit the scope of this chapter to cases where variations in the cycle time are highly dependent on the worker's work pace and not on other factors such as equipment speed variability. This typically implies a setting with highly repetitive, standardized jobs so that the worker is able to accurately estimate how his effort and performance are positively related. Furthermore, we consider only cases where the worker can perform his or her tasks without being "starved" by assuming an infinite buffer of raw materials or picking orders waiting to be processed at the worker's station. Lastly, we assume that workers have experience with the tasks and receive continuous feedback regarding their progress towards the goal and the time deadline so that they can continuously adjust their work pace to suit their needs. These assumptions can be realistic for a large number of productive environments including order picking in warehouses, assembly work and call centers for advertisements, among others.

Throughout the rest of this chapter we will use the following notation: $s(t)$ and $\dot{s}(t) = ds/dt$ are the cumulative work and work pace respectively, evaluated at time $t$ such that $t \in [0, D]$. On occasion, we omit the time arguments when referring to the cumulative work and work pace functions for enhanced readability.

## 3.4 Utility functions and assumptions

In formulating the decision making problem that the worker faces when selecting his work pace, we need to review the sources of motivation a worker can have under the influence of goals. Following Vroom's (1964) widely used distinction (see Chapter 2) on sources of motivation, we consider intrinsic and extrinsic sources of motivation. An intrinsic source of motivation is inherent to the operational task itself and thus a given effort level has a certain intrinsic desirability measure given. An extrinsic source of motivation is derived by using the goal assigned externally as a reference point for comparing the individual's own performance. In Sections 3.4.1 and 3.4.2 we show how to mathematically describe both types of motivation, providing stylized utility (i.e. preference) functions for given levels of work pace and performance respectively. We base our analysis on the desirable properties for such functions as found in the psychological and ergonomics literature. To keep the mathematical descriptions of utility functions as general as possible we also avoid any specific formulation of the utility functions making use of only desirable properties formulated as assumptions. These assumptions are summarized in Table 3.1 at the end of the section.

In this chapter, we will not propose hypotheses for the questions referring to interaction effects between different skill and goal levels (i.e. Questions 3 and 7) as these would require additional formulations that would render the conclusions too specific. We will also address these questions empirically in a laboratory study described in Chapter 4.

### 3.4.1 Utility rate - work pace function

Working at a certain speed involves physiological and psychological stress (Landy et al., 1994). To our knowledge, there are few studies where the desirability of a given work pace by individuals has been studied. However, general theories are available that can help shed light on this. The person-environment fit theory (Pervin, 1968) posits that individuals who match the environment on particular characteristics such as an assigned work pace will be the most satisfied. This implies that individual preferences exist for a given work pace.

To model these preferences, we define a function that assigns a given work pace with a given level of desirability which we refer to as the utility rate:

**Definition 1** $R(\dot{s}) : \mathbb{R}^+ \longrightarrow \mathbb{R}$ *is a continuous function that relates the possible work pace levels* $\dot{s} \in [0, L)$, *where* $L \in \mathbb{R}^+$*is the minimum unattainable work pace of an individual in a given working context with a utility rate measure* $R(\dot{s}) \in \mathbb{R}$.

We note that $R(\dot{s})$ is defined as a utility rate measure, and not as a utility measure for unit consistency when comparing the utility derived from a given amount of work accomplished, $s(t)$. We then consider that a worker derives utility (positive or negative) from working at given work pace by working continuously for a given period. Thus, working for a period twice as long at the same work pace yields twice the utility. The utility rate measure is still of a cardinal type such that for any two work pace levels $\dot{s}_1, \dot{s}_2 \in [0, L)$, $R(\dot{s}_2) \leq R(\dot{s}_1)$, if and only if $\dot{s}_1$ is preferred over $\dot{s}_2$ (i.e. $\dot{s}_2 \preceq \dot{s}_1$).

To characterize the basic properties of a utility rate function of work pace, we draw from a number of studies on job stressors noting that working at a given work pace is a job stressor because the individual exerts demands on his own body by working at a certain work pace. We draw first from Yerkes' and Dobson's Law (1908) where a given level of stressor is related to a performance level in an inverted U-shape manner. Similarly, the inverted U relationship between stressor and performance has also been reported in the literature on ergonomics (Hancock, 1986), operations management (Bendoly and Prietula, 2008) and marketing (Singh, 1998). The inverted U shape stems from the combination of two effects: the stimulation that a higher performance provides (i.e. non-boring work referred to as hypostress by Hancock and Warm (1989)) and the costs associated with higher levels of effort (and work pace), including discomfort and fatigue.

The inverted U shape is further supported by reports from the literature that workers complain of a work pace being too slow or too fast when the work pace is externally controlled (Gunnarsson and O. Östberg, 1977) as in belt conveyor production environments. The fact that workers complain of a work pace being "too slow" or "too fast" suggests that there may be an intermediate most preferred work pace. Furthermore, a study of Jansen and Kristof-Brown (2005) shows that when the tendency of an individual is to work at a pace matching his coworkers' average pace, then the individual's satisfaction is maximum, implying that the worker is most satisfied and thus, a work pace with a maximum level of desirability (satisfaction) exists. Following the above evidence, we formulate the following properties (assumptions) that an intrinsically desired work pace function, $R(\dot{s})$, should have:

**Assumption 1** $R(\dot{s})$ *is concave.*
**Assumption 2** $R(\dot{s})$ *reaches a maximum at the natural work pace denoted by* $n \in \mathbb{R}^+$. *This means that* $\arg(\max_{\dot{s} \in S} R(\dot{s})) = n$ *with* $R(\dot{s}) > 0$ *if* $\dot{s} < n$ *and* $R'(\dot{s}) < 0$ *if* $\dot{s} > n$.

Nonetheless, to complete the description of an intrinsic desirability work pace function, $R(\dot{s})$, it is important to take into account the limits of ability or skill. In this respect, Hancock and Warm (1989) define zones of instability where it is infeasible to sustain a certain stressor level for long periods and the stressor level itself is highly undesirable. In the context of work, the zones of instability define the zone adjacent to an absolute upper limit work pace $L$. This implies that working close to the upper limit work pace $L$ is extremely undesirable because of the discomfort, fatigue and even pain that might be felt when working very close to the absolute maximum capacity as evidenced by studies in fatigue (Konz, 1998) and discomfort (Dul et al., 1994). Close to the natural work pace, however, the level of satisfaction is also close to the maximum level of desirability. This would be referred by Hancock and Warm (1989) as the stable region where $R'(\dot{s}) \approx 0$. Thus, we make a third assumption for $R(\dot{s})$ and restrict the domain of the function to $[0, L)$:

**Assumption 3** *There is an $L \in \mathbb{R}^+$ such that a one sided limit exists when an increasing $\dot{s}$ approaches $L$:* $\lim_{\dot{s} \uparrow L^-} R(\dot{s}) = -\infty$.

This third assumption assures that no matter what measure of extrinsic motivation there is, the work pace may not equal that of the limit of his ability, $L$. Although Hancock and Warm (1989) also propose a lower limit of stressor level, this is not applicable for work pace as a stressor. Instead, this is applicable to cases where low stressors are critical such as in the case of low temperature or low humidity. A work pace lower than the natural work pace is bound to cause boredom and is thus undesirable. The only lower limit of work pace is the one physically possible: a null work pace. In any case, as in this paper we deal with goal setting for enhancing performance, we do not force workers to work at a work pace lower than their natural work pace and thus any further characterization of the $R(\dot{s})$ for $\dot{s} \in [0, n)$ is not needed. In Figure 3.1 we show a sketch of a characteristic $R(\dot{s})$ function that incorporates all the formal assumptions made.

For simplicity we assume that if the skill level $L$ is increased by $\phi \geq 0$, a shift in the function $R(\dot{s})$ occurs such that the most comfortable work pace is now at $n + \phi$. This assumption is not only convenient but is supported in a recent study by Bendoly and Prietula (2008) where a non-monotonic relationship between effort exerted (stressor) and motivation (desirability) levels is shifted with an increase in skill level. We formalize this assumption as follows:

**Assumption 4** *Given two skill levels $L_2$ and $L_1$ such that $L_2 = L_1 + \phi$ and $\phi > 0$, for any $\dot{s} \in [\phi, L_2)$ the corresponding utility rate–work pace functions for each skill level, $R_{L_2}(\dot{s})$ and $R_{L_1}(\dot{s})$, are related as follows: $R_{L_2}(\dot{s}) = R_{L_1}(\dot{s} - \phi)$.*

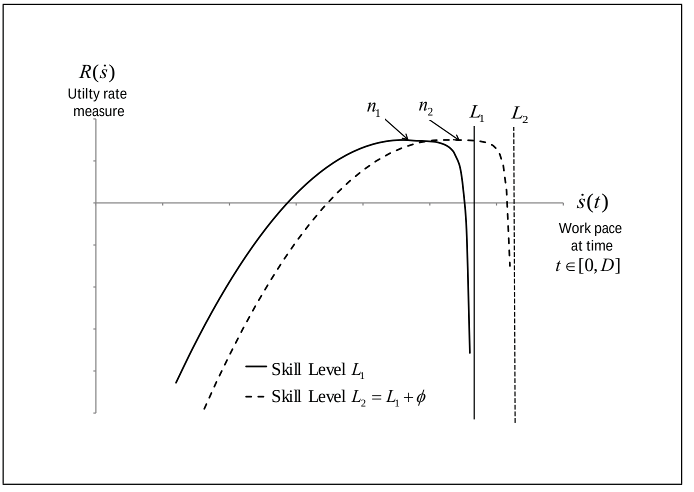



Figure 3.1: Utility rate - work pace function

### 3.4.2 Utility - performance evaluation function

When an external goal is assigned, a sense of direction is given (Locke and Latham, 1990); workers are *induced* to strive for that goal. In Heath et al. (1999), it is shown through a questionnaire of hypothetical scenarios that external goals serve as reference values that separate positive and negative evaluations of performance with respect to the goal. This means that when workers are committed to the goal, they will evaluate their performance with respect to the goals assigned. Thus, it is reasonable to assume that workers are committed to their goal when it is realistic, assigned by a recognized authority and they believe positive outcomes can be derived from achieving the goal (Locke and Latham, 1990).

**Definition 2** *We define a performance preference function, $P(s) : \mathbb{R}^+ \longrightarrow \mathbb{R}$ as a strictly increasing continuous function that assigns to cumulative work $s(t) \geq 0$ at time $t \in [0, D]$ a utility level such that given two work levels $s_2$ and $s_2$, $s_2$ is preferred over $s_1$ if $P(s_2) > P(s_1)$.*

We then consider that a worker derives utility by comparing his actual performance $s(t)$ at time $t \in [0, D]$ with the assigned goal $G$. The utility measure is of a cardinal type such that for any two possible performance levels $s_1, s_2 \in [0, +\infty)$, $P(s_2) \leq P(s_1, +\infty)$, if and only if $s_1$ is preferred over $s_2$ (i.e. $s_2 \preceq s_1$). Borrowing from Kahneman & Tversky's prospect theory (see Kahneman and Tversky, 1979; Tversky and Kahneman, 1981 and Tversky and Kahneman, 1992), we posit basic properties that a typical progress S-shaped evaluation function $P(s)$ should have if the goal $G$ is assigned:

**Assumption 5** *The assigned goal $G > 0$, behaves as a reference point such that $P(G) = 0$, dividing the set of possible performance into successes and failures. This means that if for $t \in [0, D]$, $s(t) > G$, then the progress of the work is evaluated positively $P(s) > 0$. Likewise, if the cumulative work achieved at a certain time $t \in [0, D]$ is smaller than the goal $s(t) < G$, then the progress of the work is evaluated negatively $P(s) < 0$.*
**Assumption 6** *$P(s)$ exhibits the loss aversion property such that $P(G + \delta) \leq -P(G - \delta)$ for $\delta \geq 0$. Further, $P(s)$ exhibits the strong loss aversion property: $P'(G + h) < -P'(G - h)$ for $h > 0$. In goal setting terms this implies that workers evaluate at a certain time $t \in [0, D]$ that underachieving a goal is so undesirable, that over-achieving a goal by a similar magnitude $\delta$ will not offset such undesirability.*
**Assumption 7** *$P(s)$ exhibits diminishing sensitivity of returns such that $P^{''}(s) \geq 0$ for $s \leq G$ and $P^{''}(s) < 0$ for $s > G$. The increased desirability (undesirability) of producing more (less) than the goal is reduced the more distant the cumulative performance is from the goal.*

In Behavioral Economics, the validity of the basic properties of the value function has been extensively examined through experiments that evaluate the decisions of people (see Tversky and Kahneman, 1992). The application to the domain of goals has not been entirely validated. Nonetheless, Heath (1999) and See et al. (2006) provide evidence for the applicability of the use of the prospect theory value curve in describing the way how people evaluate their performance with respect to a goal. Heath et al. (1999) present individuals with hypothetical scenarios of performance and goals which they need to compare in terms of their desirability. See et al. (2006) provide indirect evidence of the S–shaped curve as they show that running extra meters or persisting longer in a wall-sit study is more valuable the closer the subjects are to the goal. In Figure 3.2, we show how a typical evaluation curve $P(s)$ may look if Assumptions 5, 6 and 7 hold.

In addition, we include an assumption concerning extreme values of performance, where the goal meaningfulness is lost and thus we assume that no further utility can be derived from increasing performances that are "far beyond" what the goal requires:

**Assumption 8** *For a finite goal $G$, $\lim_{s \to \infty} P^{'}(s) = 0$*

Finally, to characterize the effect of changing goals in extrinsic motivation we require an additional assumption. Since the goal serves as the reference point, if the goal shifts, we may assume that the reference point also shifts. If in addition, for the sake of parsimony we assume that the characteristic extrinsic motivation utility curve remains unchanged, we can then formulate the following assumption which has also been used in See et al. (2006) and Heath et al. (1999); note that we introduce the sub-index to denote the membership of the extrinsic motivation function at a given goal level:

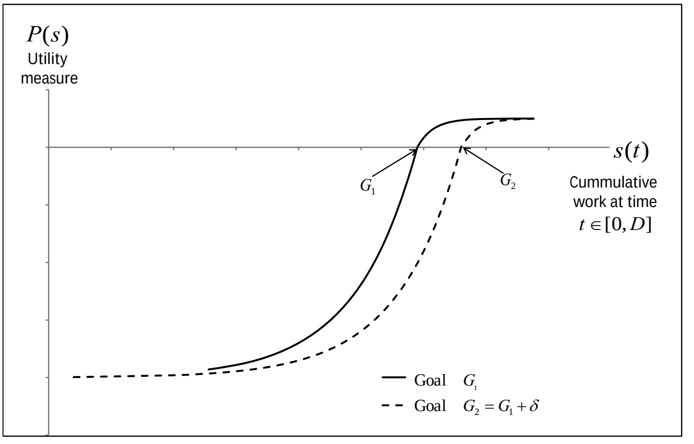



Figure 3.2: Utility - performance evaluation function

**Assumption 9** *Given two goals $G_1$ and $G_2$ such that, $G_2 = G_1 + \delta$ where $\delta \geq 0$,then the corresponding utility - performance functions, $P_{G_1}(s)$ and $P_{G_2}(s)$, are related as follows: $P_{G_2}(s) = P_{G_1}(s - \delta)$.*

## 3.5 Myopic model

We propose two modeling approaches, based on two alternative assumptions, to select the work pace. In the first approach, the worker is assumed to be myopic and only considers the utility he can derive on the spot to select his work pace and therefore continuously re-evaluates his decision until the deadline $D$. In the second approach, the worker is assumed to be a time-consistent planner (Pollak, 1968) and hence selects how he is going to regulate his work pace until the deadline $D$ at the start of the working period at time $t = 0$. We note that although both assumptions are simplistic and extreme, this has been done to derive stylized patterns of behavior and later compare them to actual ones given the results reported in Chapter 4.

To engender logical flow, we first derive those hypotheses that pertain to myopic work pace regulation and individual performance in this section and then in Section 3.6 derive those that pertain to planned work pace regulation and individual performance. The derived hypotheses of both models (i.e. myopic and planning models) are then organized per stated research question in Section 3.2.

When we assume that the worker is myopic, basing his decision of work pace on the instantaneous utility derived at time $t \in [0, D]$, we also assume that his decision needs to be revised continuously for the whole period $[0, D]$. The worker considers dynamically both the intrinsic utility rate that a given work pace provides $R(\dot{s})$ and the *instantaneous* change in utility derived

Table 3.1: Overview of assumptions for models and support from literature

| | Assumptions | Supporting literature |
|---|---|---|
| | **Intrinsic motivation function $R(\dot{s})$** | |
| A1 | $R(s)$ is concave. | Yerkes's and Dobson's Law (1908) |
| A2 | $R(s)$ reaches a maximum at the natural work pace of the worker denoted by $\dot{s} = n$; i.e. $R'(\dot{s}) > 0$ if $s < n$ and $R'(\dot{s}) < 0$ if $\dot{s} > n$. | Gunnarsson and Osberg (1977); Yerkes's and Dobson's Law (1908) |
| A3 | $\lim_{s_L} R(\dot{s}) = -\infty$. | Dul, (1994); Hancock and Warm (1989). |
| A4 | Given two skill levels $L_2$ and $L_1$ such that $L_2 = L_1 + \phi$ and $\phi > 0$, the corresponding work pace functions result in $R_{L_2}(s) = R_{L_2}(s + \phi)$. | Bendoly and Prietula (2008) |
| | **Extrinsic motivation function $P(s)$** | |
| A5 | Reference point $P(G) = 0$: If the workers achieve the goal they achieve their expectations. If the cumulative work achieved at a certain time $t \in [0, D]$ is less than the goal $s(t) < G$, then the progress of the work is evaluated negatively $P(s) < 0$ otherwise is evaluated non-negatively. | Heath (1999); See et al. (2006); Kahneman & Tversky's prospect theory (1979) |
| A6 | Loss aversion $P(G+\delta) = -P(G-\delta)$ for $\delta = 0$ and strong loss aversion $P'(G + \delta) = P'(G - \delta)$: Workers evaluate at a certain time $t \in [0, D]$ that underachieving a goal as being so undesirable, that overachieving a goal by a similar magnitude d will not offset the undesirability of the underachievement. | Heath (1999); See et al. (2006); Kahneman & Tversky's prospect theory (1979) |
| A7 | Diminishing sensitivity $P''(s) = 0$ for $s = G$ and $P''(s) < 0$ for $s > G$: The increased desirability (undesirability) of producing further more (less) than the goal is reduced the more distant the cumulative performance is from the goal. It is because of this property that utility functions of prospect theory are S-shaped. | Heath (1999); See et al. (2006); Kahneman & Tversky's prospect theory (1979) |
| A8 | For a finite goal $G$, $\lim_{s\to\infty} P'(s) = 0$. | Original assumption |
| A9 | Given two goals $G_1$ and $G_2$ such that, $G_2 = G_1 + \delta$ where $\delta = 0$,then $P_{G_2}(s) = P_{G_1}(s - \delta)$. | See et al. (2008) and Heath et al. (1999) |

from making progress evaluated with the function $P(s)$. If we assume that the total utility rate derived at time instant $t \in [0, D]$ is additive separable in the utility derived from achieving a given level of performance and at a given work pace, we define the dynamic problem of selecting the most preferred work pace $\dot{s}(t)$ by a myopic worker as follows:

$$\max_{\dot{s}(t)}[P'(s(t))\dot{s}(t) + R(\dot{s}(t))] \quad \forall t \in [0, D] \tag{3.1}$$

with initial conditions:

$$s(0) = 0 \tag{3.2}$$

Note that $P(s(t))$ is in utility units whereas $R(\dot{s}(t))$ is in utility *rate* units, so to combine both sources of motivation, the unit consistency is maintained by applying the chain rule as follows:

$$\frac{dP(s)}{dt} = \frac{dP(s)}{ds}\frac{ds}{dt} = P'(s)\dot{s} \tag{3.3}$$

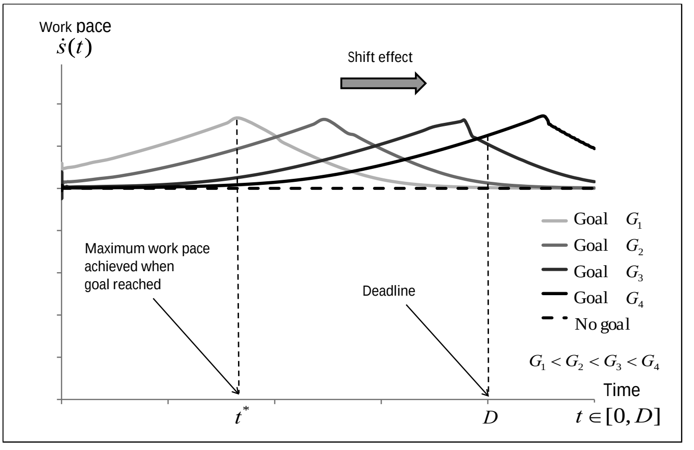



Figure 3.3: Work pace regulation myopic model hypothesis

With the decision problem given with Equations 3.1 and 3.2, we now derive hypotheses for myopic workers.

### 3.5.1 Myopic model work pace regulation

In this sub-section we start our analysis by addressing the question *"How is the work pace regulated under the influence of a given goal and deadline?"* (Question 4). For this, we characterize the work pace of a worker regulated by a myopic assumption with the following hypothesis.

**Hypothesis 1** *Given a myopic worker under influence of an assigned goal and deadline, we hypothesize that a worker will accelerate towards the assigned goal, reaching its maximum work pace when he reaches the goal and then decelerate converging to the natural work pace if enough time is allowed (see Figure 3.3).*

The intuitive reason for this acceleration towards the goal is that as the goal becomes closer, the worker derives more excitement from making progress — as the utility performance function suggests. This hypothesis is then consistent with that of Hull's (1932) goal gradient hypothesis.

For a myopic worker we denote $\dot{s}^*(t)$, $\forall t \in [0, D]$ as the optimal work pace control policy such that $\dot{s}^*(t) = \arg(\max_{\dot{s}(t)}[P^{'}(s(t))\dot{s}(t) + R(\dot{s}(t))])$. Consequently, we define $\ddot{s}^*(t)$ such that $\ddot{s}^*(t) = \frac{d\dot{s}^*(t)}{dt}$ and $s^*(t)$, such that $s^*(t) = \lim_{x \to t^-} \int_0^x \dot{s}^*(u)du$. Moreover, if we denote the time where the maximum work pace is achieved as $t^*$ such that $t^* = \arg(\max_{t \in [0,D]} \dot{s}^*(t))$, Hypothesis 1 is equivalent to the following theorem:

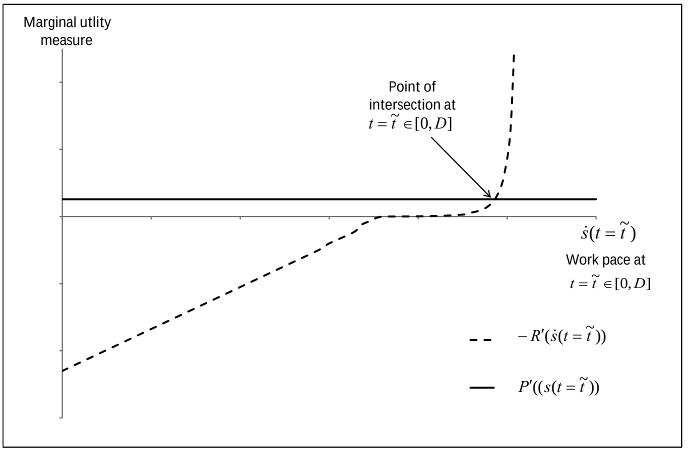



Figure 3.4: Work pace selection in the myopic model

**Theorem 1** *For a myopic worker,* $s^*(t^*) = G$ *iff* $t^* < D$*, otherwise* $t^* = D$*. Further,* $\ddot{s}^*(t) > 0$ *iff* $s^*(t) < G$ *and* $\ddot{s}^*(t) < 0$ *iff* $s^*(t) > G$*. Finally, in the absence of a deadline* $\lim_{t\to\infty} s^*(t) = n$*.*

**Proof** To prove this theorem we first solve the satisfaction maximization problem faced by a myopic worker described in Equations 3.1 and 3.2. Next, we verify that feasible unique solutions of $\dot{s}^*(t)$ can be obtained for $t \in [0, D]$. Knowing how $\dot{s}^*(t)$ evolves for $t \in [0, D]$, we then analyze when $\dot{s}^*(t)$ reaches a maximum. Finally, we prove the limiting behavior of work pace.

*Step 1* To solve the decision-making problem, it is key to observe that at a given time $t \in [0, D]$, the cumulative work $s(t)$ is independent of the instantaneous work pace $\dot{s}(t)$, and thus $\frac{ds}{d\dot{s}} = 0$. Hence, applying first order conditions the following result is obtained:

$$P^{'}(s(t)) = -R^{'}(\dot{s}(t)) \quad \forall t \in [0, D] \tag{3.4}$$

Second order conditions confirm that a local minimum exists, because $R^{''}(\dot{s}) < 0$. There is also only one possible solution to Equation 3.4 as $P^{'}(s) > 0$ (see Definition 2) and $-R^{'}(\dot{s}) < 0$ iff $\dot{s} > n$. The result in Equation 3.4 implies that the optimum work pace at any time $t \in [0, D]$ is obtained when the marginal utility of the goal induced preference function is equal to the marginal disutility rate of the work pace preference function. This result is, in fact, the dynamic equivalent to the result obtained in Wu et al. (2004) where an extra task is to be executed until the marginal cost exceeds the marginal benefits of executing the extra task. We do remark here that for a given $t = \tilde{t} \in [0, D]$, $P^{'}(s^*(t))$ is constant, remaining to define $\dot{s}^*(t)$ for Equation 3.4 to hold as shown in Figure 3.4.

*Step 2* To verify that the myopic model indeed provides feasible solutions we need to show that $s^*$ is an increasing function of $t \in [0, D]$. If we show that $\dot{s}^*(t) \geq n$ for $t \in [0, D]$, we will solutions because $s^*(0) = 0$.

We can show that $\dot{s}^*(t) \geq n$ for $t \in [0, D]$ as follows. If $\dot{s}^*(t) < n$ Equation 3.4 will not hold because on one hand, the utility performance function is strictly increasing (i.e. $P^{'}(s^*) > 0$) and on the other, it is known from the concavity of the utility rate work pace function Assumption 1 that $-R^{'}(\dot{s}^*) < 0$, making the equality impossible. If, on the other hand, $\dot{s}^*(t) \geq n$ for $t \in [0, D]$ then $-R^{'}(s^*) > 0$ and thus, Equation 3.4 may hold.

If we further impose that neither $P^{'}(s) > -R^{'}(\dot{s})$ nor $P^{'}(s) < -R^{'}(\dot{s})$ (that follows from Assumptions 1, 2, 6 and 7) holds for *all* $(s, \dot{s})$ pairs (in other words there is a switching point) such that $s \geq 0$ and $\dot{s} > n$, it is possible to guarantee that Equation 3.4 holds and that a feasible finite work pace exists.

*Step 3* To show that $s^*(t^*) = G$ iff $t^* \leq D$ we first show that $P^{'}(s^*)$ attains a maximum at $s^*(t) = G$ provided $t \leq D$ and then use this result in Equation 3.4.

*Step 3a* To identify when $P^{'}(s)$ attains a maximum we first must note that because of Assumption 6 a discontinuity of $P^{'}(s)$ may occur at $s(t) = G$. Hence, to prove when $P^{'}(s)$ achieves a maximum we first identify when $P^{'}(s)$ achieves a maximum if $s \leq G$ and if $s > G$ separately. Finally, we compare both maxima obtained for each distinct segment to establish when $P^{'}(s)$ a maximum.

From Assumption 7, $P^{'}(s)$ increases as $s(t)$ increases (and $t$ increases–verified in Step 2) reaching $P^{'}(s)$ a maximum value at $s = G$ as long as $s \leq G$. Next, when $s > G$, by Assumption 7, $P^{'}(s)$, decreases $s(t)$ increases (and $t$ increases-verified in Step 2). Thus, for $s > G$, a maximum will be attained at $s = \lim_{h \to 0} G + h$ where $h > 0$.

To combine the result of both segments of $P^{'}(s)$ we use the strong loss aversion property *(A6)*: $P'(G + h) < -P'(G - h)$ for $h > 0$. This results in $\max_{s_1} P^{'}(s_1) > \max_{s_2} P^{'}(s_2)$ where $s_1 \leq G$ and $s_2 > G$, as $G = \arg(\max_{s_1} P^{'}(s_1))$. Hence, $P^{'}(s)$ attains a maximum at $s(t) = G$.

*Step 3b* For finding the maximum work pace, we first define $g(.)$ as the inverse function of $R^{'}(\dot{s})$, valid only for $\dot{s} \geq n$, such that $\dot{s} = g(R^{'}(\dot{s}))$. Thus, because of Assumption 2 and Equation 3.4 it follows that $\dot{s}^* = g(-P^{'}(s^*))$ is an increasing function in $P^{'}(s^*)$. Combining the facts that $P^{'}(s^*)$ attains a maximum at $s^*(t) = G$ iff $t^* < D$ and that $\dot{s}^* = g(-P^{'}(s^*))$ is an increasing function in $P^{'}(s^*)$, the desired result is proven: $s(t^*) = G$ iff $t^* < D$.

Furthermore, we note that because $\dot{s}^* = g(-P^{'}(s^*))$ is an increasing function in $P^{'}(s^*)$ and because from Assumption 7, $P^{''}(s^*) > 0$ for $s^* < G$, we can conclude that the work pace, increases until the goal is reached. Similarly, because $\dot{s}^* = g(-P^{'}(s^*))$ is an increasing function in $P^{'}(s^*)$ and because from Assumption 7, $P^{''}(s^*) < 0$ for $s^* < G$, we can conclude that the work pace, increases until the goal is reached. Hence, if $s^*(D) \leq G$, the maximum work pace is reached at $t^* = D$.

*Step 4* In finding limiting work pace we show that $\lim_{t\to\infty} \dot{s}^*(t) = n$, or equivalently that $\lim_{t\to\infty}(\arg(\max_{\dot{s}(t)}[P^{'}(s)\dot{s}+R(\dot{s})])) = n$. Given that from Equation 3.4, $R^{'}(\dot{s}) = -P^{'}(s)$, taking the limit at both sides of the equation and using Assumption 8 we obtain, $\lim_{s\to\infty} R^{'}(s) = 0$ Next, since we know that from Assumption 2, $R(s)$ reaches a maximum at $s^* = n$ with $R^{'}(s^*)$ $= 0$, the desired results follows: $\lim_{t\to\infty} \dot{s}^*(t) = n$. □

### 3.5.2 Effects of varying goals on work pace regulation

Continuing with the analysis of the work pace regulation of a myopic worker, we address the question "*What are the effects on work pace regulation if the goal difficulty (level) is increased?*" (Question 5). The answer to this question is given in two hypotheses (2 and 3) that complement each other by the former indicating a shift effect in work pace regulation and the latter a different initial work pace. We state Hypothesis 2 as follows:

**Hypothesis 2** *For a myopic worker, the effect of increasing the assigned goal is to shift the work pace selected for the whole period by a constant lapse in time (see Figure 3.4).*

This hypothesis assures consistency with acceleration towards the goal effect, first posited by Hull (1932). It does so by acknowledging that when the goal is increased, the maximum work pace will be attained at a later time. The basis for this hypothesis is that we assume that the shape of the utility performance function remains unchanged and is only shifted. This means that when a new goal is assigned, the same utility measure is derived from a level of performance that is equal to the former one plus the difference between the new and old assigned goal.

If $\dot{s}^*_{G_2}(t)$ and $\dot{s}^*_{G_1}(t)$ indicate the selected work pace for each assigned goal at time $t \in [0, D]$ respectively (with $s^*_{G_2}(t)$ and $s^*_{G_1}(t)$ as cumulative work), Hypothesis 2 is equivalent to the following mathematical theorem:

**Theorem 2** *Given a $\delta > 0$ and two assigned goals $G_2, G_1 \in \mathbb{R}^+$, such that $G_2 = G_1 + \delta$, the following will hold for a myopic worker: $\dot{s}^*_{G_2}(\tau) = \dot{s}^*_{G_1}(\tau - \theta)$, where $\theta$ is a time-invariant shift and $\tau$ is a free parameter of time that is allowed to vary such that $0 \le \tau \le D - \theta$.*

**Proof** To prove that $\dot{s}^*_{G_2}(\tau) = \dot{s}^*_{G_1}(\tau-\theta)$, we first define an equivalent relationship to be proven. Next, we prove the equivalent relationship.

*Step 1* We first provide an equivalent definition of $\theta$, such that $\theta$ is also the fixed time required to achieve a total work of $\delta$ for an individual assigned to goal $G_1$ such that $\delta = \int_0^\theta \dot{s}^*_{G_2}(t)dt$. Then we also define $\omega(\tau)$ as a time shift that allows the following relationship to hold such that $0 \le \tau \le D - \theta$:

$$\int_0^{\tau+\omega} \dot{s}^*_{G_2}(t)dt = \int_0^{\tau} \dot{s}^*_{G_2}(t)dt + \delta \tag{3.5}$$

Note then that as $\dot{s}^*_{G_2}(\tau + \omega(\tau))$ (in the left hand side of the equation) and $\dot{s}^*_{G_1}(\tau)+ \delta$ (the right hand side of the equation) are both increasing functions on $\tau$, the equality will hold for some positive $\omega(\tau)$ as $\delta > 0$. As, a priori $\omega(\tau)$ is a time shift that is not necessarily time-invariant, if we show that $\theta = \omega(\tau)$, it means that $\omega(\tau)$ is also time-invariant as $\theta$ is a fixed time independent of $\tau$. Thus, we want to then show that $\theta = \omega(\tau)$, because this is equivalent to show that $\dot{s}^*_{G_2}(\tau) = \dot{s}^*_{G_1}(\tau - \theta)$ for a given $\delta > 0$.

*Step 2* To show that $\theta = \omega(\tau)$, we first take derivatives at both sides of the equation in Assumption 9 and then apply inverse function $g(-x)$ to both sides for $t \in [0, D]$ obtaining:

$$g(-P'_{G_2}(s^*_{G_2}(t + \omega(\tau))) = g(-P'_{G_1}(s^*_{G_2}(t + \omega) - \delta)) \tag{3.6}$$

Noting that in Equation 3.5 it holds that $s^*_{G_2}(t + \omega) = s^*_{G_1}(t) + \delta$, from the right hand side of Equation 3.6 we have that for $t \in [0, D]$:

$$g(-P'_{G_1}(s^*_{G_2}(t + \omega(\tau)) - \delta)) = g(-P'_{G_1}(s^*_{G_1}(t))) \tag{3.7}$$

Using the fact that $\dot{s}^* = g(-P^{'}(s^*))$ we obtain from the right hand side of Equation 3.7 that for $t \in [0, D]$:

$$g(-P'_{G_1}(s^*_{G_1}(t))) = s^*_{G_1}(t) \tag{3.8}$$

Next, noting that the left hand side of Equation 3.5 is $g(-P'_{G_2}(s^*_{G_2}(t+\omega)) = \dot{s}^*_{G_2}(t+\omega)$, and combining it with the result in Equation 3.8, we find that for $t \in [0, D]$ the following holds:

$$\dot{s}^*_{G_1}(t) = \dot{s}^*_{G_2}(t + \omega(\tau)) \tag{3.9}$$

Next, we substitute $\dot{s}^*_{G_1}(t)$ in Equation 3.5 using Equation 3.9 obtaining the following:

$$\int_0^{\tau+\omega(\tau)} \dot{s}^*_{G_2}(t)dt = \int_0^{\tau} \dot{s}^*_{G_2}(t + \omega(\tau))dt + \delta \tag{3.10}$$

Integrating we obtain:

$$s^*_{G_2}(\tau + \omega(\tau)) = s^*_{G_2}(\tau + \omega(\tau)) - s^*_{G_2}(\omega(\tau)) + s^*_{G_2}(\theta) \tag{3.11}$$

Rearranging we prove the desired result, $\theta = \omega(\tau)$ such that $0 \leq \tau \leq D - \theta$. □

Simultaneous to the effect of shifting the work pace over time, increasing the goal difficulty may also have the somewhat counter-intuitive effect of decreasing the starting work pace.

**Hypothesis 3** *When a higher goal is assigned, myopic workers will start working at a lower work pace.*

Although this hypothesis may, at first glance, seem counter-intuitive, its underlying justification is that the lower goals are assigned, the closer the worker is to achieving these right from the start of the working period. As we assume in Assumption 7 that the closer the worker is to accomplish goal, the greater the marginal returns on making progress are, it then follows that the worker is more motivated to perform at a higher work pace at the start of work when the assigned goal is lower.

Formally, Hypothesis 3 can be re-written as the following theorem:

**Theorem 3** *Given a $\delta > 0$ and two assigned goals $G_2$, $G_1 \in \mathbb{R}^+$, such that $G_2 = G_1 + \delta$, it holds that at $t = 0$, $\dot{s}^*_{G_2}(0) < \dot{s}^*_{G_1}(0)$.*

**Proof** For proving that $\dot{s}^*_{G_2}(0) < \dot{s}^*_{G_1}(0)$, we first note the fact that $P'_{G_2}(s^*_{G_2}(0)) < P'_{G_2}(s^*_{G_2}(0) + \delta)$ for $\delta > 0$ holds, because of the assumption of diminishing returns, Assumption 7 for $s^*(0) < G$. Next, we apply assumption Assumption 9, noting that $P'_{G_2}(s^*_{G_2}(0) + \delta) = P'_{G_1}(s^*_{G_1}(0))$. From this, it follows that $P'_{G_2}(s^*_{G_2}(0)) < P'_{G_1}(s^*_{G_1}(0))$. Using the fact that the function $\dot{s}^* = g(-P^{'}(s^*))$ is increasing on $P^{'}(s^*)$, we can then show the desired result: $\dot{s}^*_{G_2}(0) < \dot{s}^*_{G_1}(0)$. □

### 3.5.3 Effects of varying skills on work pace regulation

In this section we start our analysis by addressing the question "*What are the effects on work pace regulation if the skill level is increased under the influence of an assigned goal and deadline?*" (Question 6). For a worker assumed to be myopic, the possible effects of skill levels on work pace regulation are intuitive in terms of the work pace achieved at a given time and the maximum work pace attainable. For characterizing these effects we propose Hypothesis 4 and Hypothesis 5.

**Hypothesis 4** *Under the influence of an assigned goal and deadline, if a myopic worker has a higher skill level than another myopic worker, the selected work pace of the worker with a higher skill level is higher as long as the goal has not yet been achieved.*

We formalize Hypothesis 4 by introducing the following notation. We denote $\dot{s}^*_{L_1}(t)$ and $\dot{s}^*_{L_2}(t)$ as the work pace (with $s^*_{G_2}(t)$ and $s^*_{G_1}(t)$ as cumulative work) obtained by workers of skill level $L_1$ and $L_2$ at $t \in [0, D]$ such that $L_2 = L_1 + \phi$ and $\phi > 0$. Furthermore, we define $\hat{t}_{L_1}$ and $\hat{t}_{L_1}$such that $s^*_{L_1}(\hat{t}_{L_1}) = G$ and $s^*_{L_2}(\hat{t}_{L_2}) = G$. Similarly, we define $t^*_{L_1}$ and $t^*_{L_2}$ such that $t^*_{L_1} = \arg(\max_{t\in[0,D]} \dot{s}^*_{L_1}(t))$ and $t^*_{L_2} = \arg(\max_{t\in[0,D]} \dot{s}^*_{L_2}(t))$. Given this notation, Hypothesis 4 can be formally re-written as follows.

**Theorem 4** *Given two myopic workers with skill levels $L_1$ and $L_2$ such that $L_2 = L_1 + \phi$ and $\phi > 0$, it holds that $\dot{s}^*_{L_2}(t) > \dot{s}^*_{L_1}(t)$ and $\hat{t}_{L2} < \hat{t}_{L1}$, for $t \in [0, \hat{t}_{L2}]$. It also holds that $\dot{s}^*_{L_2}(t) > \dot{s}^*_{L_1}(t)$ for $t \in [0, D]$, if $s^*_{L_1}(t^*_{L_1}) < G$ and $s^*_{L_2}(t^*_{L_2}) < G$.*

**Proof** The proof is organized as follows, first we show that at $t = 0$, $\dot{s}^*_{L_2}(0) > \dot{s}^*_{L_1}(0)$. Next, we show by approximation, that for an arbitrarily small $h > 0$ it holds that $\dot{s}^*_{L_2}(h) > \dot{s}^*_{L_1}(h)$. Finally, we show that for $r = 1, 2, ...k$ such that $s^*(kh) \leq G < s^*((k+1)h)$, it holds that $\dot{s}^*_{L_2}(rh) > \dot{s}^*_{L_1}(rh)$.

*Step 1* To prove that $\dot{s}^*_{L_2}(0) > \dot{s}^*_{L_1}(0)$, we first note that by Assumption 4 $R'_{L_2}(\dot{s}) = R'_{L_1}(\dot{s} - \phi)$. Next, because $R''(\dot{s}) < 0$ by Assumption 1 it holds that $R'_{L_1}(\dot{s} - \phi) < R'_{L_1}(\dot{s})$ and thus $R'_{L_2}(\dot{s}) < R'_{L_1}(\dot{s})$.This implies that two inverse functions $g_{L_2}$, $g_{L_1}$ defined such that $\dot{s}_{L_1} = g_{L_1}(R'_{L_1}(\dot{s}))$ and $\dot{s}_{L_2} = g_{L_2}(R'_{L_2}(\dot{s}))$ are related as follows: $g_{L2}(x) > g_{L1}(x)$, where $x \in \mathbb{R}$. Thus, we can show that at $t = 0$, $g_{L2}(-P'(s^*(0))) > g_{L1}(-P'(s^*(0)))$ and thus by Equation 3.4, $\dot{s}^*_{L_2}(0) > \dot{s}^*_{L_1}(0)$.

*Step 2* To prove that $\dot{s}^*_{L_2}(h) > \dot{s}^*_{L_1}(h)$, we first use Euler's approximation, for an arbitrarily small $h > 0$ for estimating $s^*_{L_1}(t + h)$ and $s^*_{L_2}(t + h)$, obtaining: $s^*_{L_1}(t + h) \approx s^*_{L_1}(t) + hg(-P'(s^*_{L_1}(t)))$ and $s^*_{L_2}(t + h) \approx s^*_{L_2}(t) + hg(-P'(s^*_{L_2}(t)))$. We then note that by initial conditions at $t = 0$, $s^*_{L_1}(0) = s^*_{L2}(0) = 0$ and $P'(s^*_{L_2}(0)) = P'(s^*_{L_2}(0))$. The initial conditions combined with Euler' approximation imply then that at time $t = h$, $s^*_{L_2}(h) > s^*_{L_1}(h)$. From this, it then follows that $-P'(s^*_{L_2}(h)) < -P'(s^*_{L_1}(h))$. As $g_{L2}(x) > g_{L1}(x)$ for $x \in \mathbb{R}$ and both, $g_{L1}$ and $g_{L2}$, are decreasing functions on $x \in \mathbb{R}$, we may then conclude that $g_{L2}(-P'(s^*_{L_2}(h))) < g_{L1}(-P'(s^*_{L_1}(h)))$, showing that $\dot{s}^*_{L_2}(h) > \dot{s}^*_{L_1}(h)$.

*Step 3* Here we show that $\dot{s}^*_{L_2}(rh) > \dot{s}^*_{L_1}(rh)$ for $r = 1, 2, ...k$ such that $s^*(kh) \leq G < s^*((k+1)h)$. In a similar way, we can then construct an approximation for an arbitrarily small step $h$ as follows: $s^*_{L_1}(t+2h) \approx s^*_{L_1}(t+h) + hg(-P'(s^*_{L_1}(t+h)))$ and $s^*_{L_2}(t+2h) \approx s^*_{L_2}(t+h) + hg(-P'(s^*_{L_2}(t+h)))$. At time $t = 2h$, we use the facts established in Step 2 that $s^*_{L_2}(h) > s^*_{L_1}(h)$ and that $-P'(s^*_{L_2}(h)) < -P'(s^*_{L_1}(h))$, implying then that $s^*_{L_2}(t + h) > s^*_{L_1}(t + 2h)$. Applying again inverse the function $g(x)$ to the last expression and noting that is decreasing on $x \in \mathbb{R}$ and that $-P'(s^*_{L_2}(2h)) < -P'(s^*_{L_1}(2h))$ we obtain that $\dot{s}^*_{L_2}(h) > \dot{s}^*_{L_1}(h)$.It is then easy to see that the argument (*Step 3*) can be repeated for $t = 3h, 4h, ...kh$ where $k$ is a positive integer such that $s^*_{L_2}(kh) \leq G < s^*_{L_2}((k+1)h)$, thus proving the desired result. From $s^*_{L_2}(t) > s^*_{L_1}(t)$ for $t \in [0, \hat{t}_{L2}]$, it also follows directly that $\hat{t}_{L2} < \hat{t}_{L1}$as both, $s^*_{L_1}(\hat{t}_{L1})$ and $s^*_{L_2}(\hat{t}_{L2})$ are increasing functions in $\hat{t}_{L_1}$, $\hat{t}_{L_1} \in [0, D]$.

Note also, that in case the goal cannot be achieved within the allowed time $t \in [0, D]$, *Step 3* of the proof may be repeated for $t = 3h, 4h, ...ph$, where $p$ is a positive integer such that $ph \leq t < (p + 1)$. This can be done because Assumption 7**,** $P''(s) > 0$ holds if $s < G$. Thus, $\dot{s}^*_{L_2}(t) > \dot{s}^*_{L_1}(t)$ also follows for $t \in [0, D]$ if $s^*_{L_1}(t^*_{L_1}) < G$ and $s^*_{L_2}(t^*_{L_2}) < G$ (i.e. the goal can not be achieved by a worker of either $L_1$ and $L_2$ skill levels). $\square$

Further, as a consequence of Hypothesis 4, we can also hypothesize what will happen with the maximum work pace as follows.

**Hypothesis 5** *Under the influence of an assigned goal and deadline, the maximum observed work pace increases when the skill level is increased.*

**Theorem 5** *Give two myopic workers with skill levels $L_1$ and $L_2$ such that $L_2 = L_1 + \phi$ and $\phi > 0$, it holds that $\dot{s}^*_{L_2}(t^*_{L_2}) > \dot{s}^*_{L_1}(t^*_{L_1})$ where $t^*_{L_1} = \arg(\max_{t\in[0,D]} \dot{s}_{L_1}(t))$ and $t^*_{L_2} = \arg(\max_{t\in[0,D]} \dot{s}_{L_2}(t))$ .*

**Proof** To proof $\dot{s}^*_{L_2}(t^*_{L_2}) > \dot{s}^*_{L_1}(t^*_{L_1})$ we identify three possible cases.

*Case I:* $s^*_{L_2}(t^*_{L_2}) = s^*_{L_1}(t^*_{L_1}) = G$. This means the goal can be achieved by workers at both skill levels within $t \in [0, D]$. From the proof of Theorem 4 it holds then for this case that $g_{L_2}(x) > g_{L_1}(x)$ for $x \in \mathbb{R}$ and hence it also holds that $g_{L_2}(-P'(G)) > g_{L_1}(-P'(G))$. This implies that $\dot{s}^*_{L_2}(t^*_{L_2}) > \dot{s}^*_{L_1}(t^*_{L_1})$.

*Case II*: $s^*_{L_1}(t^*_{L_1}) < G$ and $s^*_{L_2}(t^*_{L_2}) = G$. This means the goal can be achieved by the worker of skill level $L_2$, but not by the worker of skill level $L_1$ within $t \in [0, D]$. To proof $\dot{s}^*_{L_2}(t^*_{L_2}) > \dot{s}^*_{L_1}(t^*_{L_1})$, we first relax the assigned deadline, $D$ for a worker of skill level $L_1$ defining a new time at which the maximum work pace is obtained $t^r_{L_1} = \arg(\max_{t\in[0,\infty)} \dot{s}_{L_1}(t))$. From this, we obtain that $\dot{s}_{L_1}(t^r_{L_1}) > \dot{s}_{L_1}(t^*_{L_1})$, as a finite goal $G$ will at some time be achieved. However, because $g_{L_2}(-P'(G)) > g_{L_1}(-P'(G))$, it holds that $\dot{s}_{L_2}(t^*_{L_2}) > \dot{s}_{L_1}(t^r_{L_1}) > \dot{s}_{L_1}(t^*_{L_1})$.

*Case III*: $s_{L_1}(t^*_{L_1}) < G$ and $s_{L_2}(t^*_{L_2}) < G$. This means the goal cannot be achieved by workers at both skill levels within $t \in [0, D]$. The desired result follows directly from applying Theorem 1 at $t = D$ where it is known that the maximum work pace occurs, giving $\dot{s}_{L_2}(D) > \dot{s}_{L_1}(D)$.

We also note that because $g_{L_2}(\dot{s}(t)) > g_{L_1}(\dot{s}(t))$ and $\dot{s}_{L_2}(t) > \dot{s}_{L_1}(t)$, for $s_{L_1}(t) < G$, it is not possible to have a case where $s_{L_1}(t^*_{L_1}) < G$ and $s_{L_2}(t^*_{L_2}) = G$. Note also that by Theorem 1 under no circumstance, can the maximum work pace be achieved after achieving the goal. As cases I, II and III, are exhaustive, this proves the desired result. $\square$

### 3.5.4 Effects of varying goals on total work

Once the effect of varying goals in work pace regulation has been identified, the effects on total work can be identified under the myopic assumption. We therefore address the following question, "*What are the effects on individual performance (i.e. cumulative performance of an individual measure at the end of the assigned period) if the goal difficulty (level) increases?*" (Question 1):

**Hypothesis 6** *The goal difficulty-total performance relation for a myopic worker is unimodal, increasing and then decreasing on the assigned goal level.*

This goal difficulty-total performance relationship is consistent with the result of Erez and Zidon (1984). However, unlike Erez and Zidon (1984) it does not require a lack of commitment towards the goal as an explanation for why the total performance decreases if the goal exceeds a certain threshold. In the case of a myopic worker, a possible explanation for a drop in total performance when the goal exceeds a certain threshold is that a work pace regulation shift occurs when a goal is increased. When the goal cannot be attained in the allocated period, increasing the goal further results in a further shift of the work pace regulation curve. As motivation increases the closer the worker is to achieving the goal, if the goal is still far enough away when the deadline has been reached, these motivation gains will be diminished. For this reason, a "clipping effect" exists, where the benefits of enhanced motivation by reaching the goal are simply "clipped" if the goal cannot be attained before the assigned deadline (see Figure 3.3).

The following theorem describes Hypothesis 6 mathematically:

**Theorem 6** *Given an initial goal $G_1$, increasing such a goal by $\delta > 0$ such that $G_1 + \delta$, may increase total individual performance such that $\frac{ds^*(D)}{d\delta} > 0$ iff $s_{G_1}(D) < G$, being the relationship between goal increase and goal increase unimodal, such that $\frac{d^2s^*(D)}{d\delta^2} > 0$. Otherwise if $s_{G_1}(D) < G$ an increase in the goal, decreases total individual performance such that $\frac{ds^*(D)}{d\delta} < 0$.*

**Proof** To show this, we first formulate the problem of setting an optimal increment of a goal for maximizing performance as follows:

$$\max_{\delta \geq 0} \int_0^D \dot{s}^*_{G_1+\delta}(t)dt \tag{3.12}$$

Next, we use Theorem 2, $\dot{s}^*_{G_2}(\tau) = \dot{s}^*_{G_1}(\tau + \theta)$ when $G_2 = G_1 + \delta$, to re-formulate the problem of setting an optimal increase in the goal as setting an optimal shift $\theta$ as follows:

$$\max_{\delta \geq 0} \int_0^D \dot{s}^*_{G_1+\delta}(t)dt = \max_{\theta \geq 0} \int_0^D \dot{s}^*_{G_1}(t+\theta)dt \tag{3.13}$$

Evaluating the integrals yields the following problem:

$$\max_{\theta}(s^*_{G_1}(D+\theta) - s^*_{G_1}(\theta)) \tag{3.14}$$

Applying first order conditions and noting that $\frac{ds}{d\theta} = \frac{ds}{dt} \cdot \frac{dt}{d\theta}$ and $\frac{dt}{d\theta} = 1$ we obtain the following relationship:

$$\dot{s}^*_{G_1}(D+\theta) = \dot{s}^*_{G_1}(\theta) \tag{3.15}$$

In order to analyze the second order conditions, we identify two cases. In the first case, the initial goal $G_1$ is achieved before the deadline, $s^*_{G_1}(D) < G_1$. If this is the case, then $\ddot{s}^*_{G_1}(\theta) > 0$ and $\ddot{s}^*_{G_1}(G+\theta) < 0$, hence $\ddot{s}^*_{G_1}(D+\theta) - \ddot{s}^*_{G_1}(\theta) < 0$, showing the existence of a single maximum for $0 < \theta < D$. However, if $s^*_{G_1}(D) > G_1$, then $\ddot{s}^*_G(D+\theta) > \ddot{s}^*_G(\theta) > 0$, hence $\ddot{s}^*_{G_1}(D+\theta) - \ddot{s}^*_{G_1}(\theta) > 0$, implying that a positive shift with $\theta > 0$ only decreases performance and the minimum does not exist as the first order conditions will not hold. As $\theta$ increases, $\delta$ also increases, thus proving the desired result. $\square$

### 3.5.5 Effects of varying skills on total work

In this sub-section we address the question: "*What are the effects on individual performance if the skill level increases under influence of an assigned goal and deadline*?" (Question 2). For a myopic worker we propose an intuitive hypothesis:

**Hypothesis 7** *Under the influence of an assigned goal and deadline, if the skill of a myopic worker increases, the total work (performance) will increase.*

Although this hypothesis in this respect is intuitive, it's proof is non-trivial. Moreover, it is instructive to formulate a theorem and identify different cases where the gains in total individual performance are obtained when skill levels are increased. We formulate Hypothesis 7 as the following formal theorem:

**Theorem 7** *Given two skill levels $L_1$ and $L_2$ such that $L_2 = L_1+\phi$ and $\phi > 0$, the corresponding cumulative work for each skill level at the deadline, $s^*_{L_2}(D)$ and $s^*_{L_1}(D)$, are related as follows: $s^*_{L_2}(D) > s^*_{L_1}(D)$.*

**Proof** For proving Theorem 7, we follow a similar argumentation as in the proof of Theorem 5. The same cases apply as in the proof of Theorem 5 as follows:

*Case I:* $s^*_{L_2}(t^*_{L_2}) = s^*_{L_1}(t^*_{L_1}) = G$. This means the goal can be achieved by workers at both skill levels within $t \in [0, D]$. To prove the relationship for this case, we use Euler's approximation to derive the behavior of $s^*_{L_2}(D)$ and $s^*_{L_1}(D)$ for $t \in (\hat{t}_{L_1}, D]$ and $t \in (\hat{t}_{L_1}, D]$ respectively. Thus, for an arbitrarily small $h > 0$, we obtain: $s^*_{L_1}(\hat{t}_{L_1}+h) \approx s^*_{L_1}(t)+hg_{L_1}(-P^{'}(G))$ and $s^*_{L_2}(\hat{t}_{L_2}+h) \approx s^*_{L_2}(t) + hg_{L_2}(-P^{'}(G))$. We first make two observations, $s^*_{L_1}(\hat{t}_{L_1}) = \dot{s}^*_{L_2}(\hat{t}_{L_2}) = G$ and from the proof of Theorem 4 it holds that $g_{L_2}(x) > g_{L_1}(x)$ for $x \in \mathbb{R}$. From these observations it then follows that $s^*_{L_2}(\hat{t}_{L_2} + h) > s^*_{L_1}(\hat{t}_{L_1} + h)$. The approximation can then be continued for further steps of $h$ such that $t = \hat{t}_{L_1} + 2h, \hat{t}_{L_1} + 3h...\hat{t}_{L_1} + mh$ and $t = \hat{t}_{L_2} + 2h, \hat{t}_{L_2} + 3h...\hat{t}_{L_2} + mh$ such that for a positive integer $m$ it holds that $\hat{t}_{L_1} + mh < D < \hat{t}_{L_1} + (m+1)h$. As $\lim_{h\to 0}$ $\hat{t}_{L_1} + mh = D$, we then proved that $s^*_{L_2}(\hat{t}_{L_2} + (D - \hat{t}_{L_1}) > s^*_{L_1}(D)$.

We also note that as $\hat{t}_{L_2} < \hat{t}_{L_1}$, it holds $\hat{t}_{L_2}+(D-\hat{t}_{L_1}) < D$. Since $s^*_{L_2}(t)$ is increasing in time $t \in [0, D]$ (from the proof of Theorem 1), it follows that $s^*_{L_2}(\hat{t}_{L_2}+(D-\hat{t}_{L_1}) > s^*_{L_2}(\hat{t}_{L_2}+(D-\hat{t}_{L_1}) > s^*_{L_1}(D)$, thus proving the desired result.

*Case II:* $s^*_{L_1}(t^*_{L_1}) < G$ *and* $s^*_{L_2}(t^*_{L_2}) = G$. This means the goal can be achieved by the worker of skill level $L_2$, but not by the worker of skill level $L_1$ within $t \in [0, D]$. Hence, by definition $s^*_{L_2}(D) > s^*_{L_1}(D)$.

*Case III:* $s^*_{L_1}(t^*_{L_1}) < G$ *and* $s^*_{L_2}(t^*_{L_2}) < G$. This means the goal cannot be achieved by workers at both skill levels within $t \in [0, D]$. We then use the fact that $s^*_{L_2}(t) > \dot{s}^*_{L_1}(t)$ for $t \in [0, D]$ if $s^*_{L_1}(t^*_{L_1}) < G$ and $s^*_{L_2}(t^*_{L_2}) < G$ from theorem Theorem 4 and integrate, obtaining: $\int_0^D \dot{s}^*_{L_2}(t)dt > \int_0^D \dot{s}^*_{L_1}(t)dt$, thus proving the desired result. □

## 3.6 Planner model

When we view workers as perfect planners, workers select their work pace taking into account the utility gain to be accumulated within the time interval $[0, D]$. This is opposed to the view of the worker exhibiting myopic behavior, where the selected work pace is based on the utility rate gained at a given instant. We refer to the planners as "perfect" in the sense that they exhibit time consistency in their preferences (Pollak, 1968) and therefore do not require a change in their plan at any later point within the interval $[0, D]$. This is of course a simplifying assumption that can later be contrasted with the work pace adjustments observed in subjects in the experiments of Chapter 4. The sources of motivation are the same as the one used in the myopic model: work pace related and goal related. As a result, we formulate the work pace selection (or equivalently, the cumulative work progress) problem faced by a planner during the interval $[0, D]$ as the following calculus of variation problem:

$$\max_{s(t)} \int_0^D [R(\dot{s}(t)) + P^{'}(s(t))\dot{s}(t)]dt \tag{3.16}$$

s.t.

$$s(0) = 0 \tag{3.17}$$

### 3.6.1 Planner model work pace regulation

For the planner model, we ask again the first question: "*How is the work pace regulated under the influence of a given goal and deadline?*" (Question 3). As the planner worker problem differs from the myopic worker problem in the way decisions are made in the time horizon it is then expected that the work pace regulation patterns would be different. In particular, we posit the following hypothesis to characterize the work pace regulation of a planner worker:

**Hypothesis 8** *Under the influence of a goal and deadline, a planner worker will regulate his work pace by selecting a time invariant work pace for the whole period that allows him to maximize his total satisfaction for the period.*

This hypothesis may intuitively be interpreted as the scenario in which a worker works at a constant work pace because when they consider the total desirability of performing for the whole time horizon, there is no attractive reason to vary the work pace. Moreover, working at two different work pace rates during the allowed time is undesirable as the derived utility is lower than the total utility derived from working at a single work pace that is in-between those selected. This is true due to the concavity of the utility-rate work pace function, $R(s)$.

This hypothesis is consistent with that of Parkinson's Law (1962) and Bryan and Locke (1967) where individuals adjust their work pace to a certain level in order to be able to obtain their goal, evidencing certain planning and anticipation of what work pace regulation policy is preferred for the whole assigned period. Simultaneously, the result does not include the acceleration effect towards the goal as in Hull (1932).

Hypothesis 8 can be re-written as the following theorem:

**Theorem 8** *Under the influence of a goal and deadline, a planner worker will work at a time invariant work pace such that* $\ddot{s}^*(t) = 0$ *and* $\dot{s}^*(t) = g(-P'(Ds(D))$*for* $t = [0, D]$ *where* $\dot{s}^*(t) = g(R^{'}(\dot{s}(t)))$.

**Proof** We prove this theorem by solving the calculus of variation model presented in Equations 3.16 and 3.17. We first remark that in solving this problem, the Euler equation can not be applied because of a possible discontinuity of the function $P'(s)$ at $s = G$ given Assumptions 6 and 7 (see Kamien and Schwartz (1991)). For this reason, we take an indirect approach. First, we observe that the second, extrinsic motivation function, related term, can be integrated by substitution, yielding the following:

$$\int_0^D [P'(s(t))\dot{s}(t)]dt = P(s(t))|_{t=0}^{t=D} = P(s(D)) - P(0) \tag{3.18}$$

Equation 3.18 implies that the value of the second term in Equation 3.16 is only dependent on the total work done at $t = D$. This means also that Equation 3.18 is independent of the specific choice of work pace $\dot{s}(t)$ at each instant $t \in [0, T]$ as long as the cumulative work at $t = D$ remains constant. As a result, the variation of the work pace over the interval $[0, D]$ is fully determined by the first term in Equation 3.18, namely the work pace preference function term:

$$\max_{s(t)} \left[ \int_0^D R(\dot{s}(t))dt + P(\int_0^D \dot{s}(t)dt) \right] \tag{3.19}$$

As $R(\dot{s})$ and its derivative $R'(\dot{s})$ are continuous, Euler's equation may be applied to obtain a maximum as follows.

$$\frac{\partial(R(\dot{s}(t)))}{\partial s} = \frac{d\left(\frac{\partial(R(\dot{s}(t)))}{\partial \dot{s}}\right)}{dt} \tag{3.20}$$

Thus, applying the chain rule, it follows that:

$$0 = \frac{dR'(\dot{s})}{dt} = R(\dot{s})\ddot{s} \tag{3.21}$$

From Assumption 1, it is known that $R(\dot{s})$ is concave, hence from Equation 3.21 it follows that

the work pace is constant as $\ddot{s}^*(t) = 0$, in the interval $t \in [0, D]$ in order to maximize total utility.

As the work pace is constant, the intrinsic motivation function $R(\dot{s})$ is also a constant for the entire interval $t \in [0, D]$. Hence, substituting in Equation 3.16 the dynamic optimization problem of the planner model can be reduced into a static one at $t = D$ (or any other arbitrary time in the interval $t \in [0, D]$):

$$\max_{\dot{s}(D)} R(\dot{s}(D))D + P(D\dot{s}(D)) - P(0) \tag{3.22}$$

Applying first order conditions we obtain:

$$R'(\dot{s}(D)) = -P'(D\dot{s}(D)) \tag{3.23}$$

Note that Equation 3.23 is similar to the marginal expression for the myopic model in Equation 3.4, with the difference that the work pace and the cumulative work are evaluated at the deadline (see Figure 3.5). Furthermore, using the same definition of $g(.)$ such that $\dot{s}(t) = g(R^{'}(\dot{s}(t)))$, the desired result, follows: $\dot{s}^*(t) = g(-P'(Ds(D))$for $t = [0, D]$. $\square$

### 3.6.2 Effects of varying goals on work pace regulation and total work

Acknowledging that the work pace is constant according to the worker planner model, conclusions that apply to effects on work pace regulation also apply to total work. Only the following simple conversion: $\dot{s}^*(t) = \frac{S^*(D)}{D}$, $\forall t \in [0, D]$ needs to be done. Therefore, in this sub-section we address the effects of varying goals on both, work pace regulation and total performance, via the following questions: "*What are the effects on work pace regulation if the goal difficulty (level) is increased?*" (Question 5) and "*What are the effects on total performance if the goal difficulty (level) is increased?*" (Question 1).

In evaluating the consequence of having a constant work pace when the worker is assumed to plan, we propose two alternative hypotheses (i.e. Hypotheses 9 and 10) to answer Questions

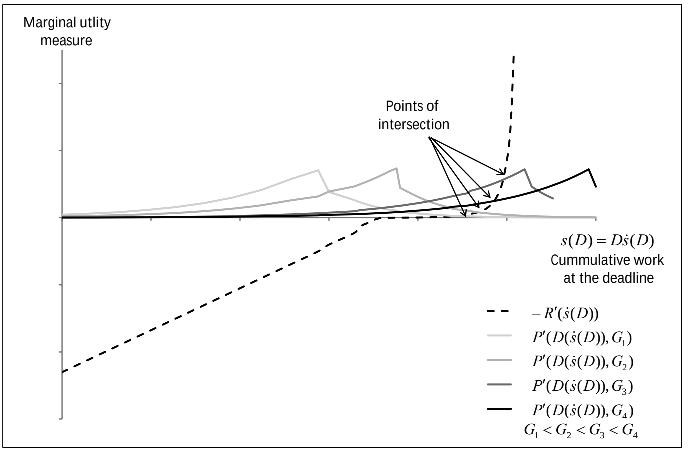



Figure 3.5: Work pace selection in the planner model

1 and 5 assuming planning behavior from the worker. Hypothesis 9 is equivalent to Hypothesis 6 for the myopic model:

**Hypothesis 9** *The goal difficulty–total performance (and constant work pace) relation for a planningworker is unimodal, increasing and then decreasing on the assigned goal level. When an assigned goal can be achieved during the allocated period, increasing the goal may increase total performance (and constant work pace). Otherwise, when an assigned goal can not be achieved, if such a goal is further increased, the goal may decrease total performance (and constant work pace).*

This hypothesis is again consistent with the relationship proposed by Erez and Zidon (1984). The intuition behind Hypothesis 9 is nonetheless different. For sufficiently high work pace levels, there is a decreasing intrinsic motivation for a higher work pace level (i.e. modeled with $R(\dot{s})$). This implies that once the maximum performance is achieved, if the goal is further increased, the selected work pace will be reduced to the point where the marginal decrements in the utility rate derived from the work pace match those of the marginal increments in the utility derived from performing with respect to the goal.

To formulate the theorem equivalent to Hypothesis 9, we then explicitly make the selected cumulative work at time $t = D$ dependent on the assigned goal $G$ as follows: $s^*(D, G)$. We can now formulate the theorem as follows:

**Theorem 9** *The individual total work function that depends on the goal is concave such that if* $D\dot{s}^*(D,G) - G < 0$, $\frac{d\dot{s}^*(D,G)}{dG} > 0$, $\frac{ds^*(D,G)}{dG} > 0$ *and if* $D\dot{s}^*(D) - G > 0$, *then* $\frac{d\dot{s}^*(D,G)}{dG} > 0, \frac{ds^*(D,G)}{dG} > 0$.

**Proof** To prove a non-monotonic goal level-performance relationship, we follow a similar procedure as the one found at Wu et al. (2004). First, we transform the utility performance function so that it is explicitly a function of the assigned goal $G$, by defining a function $V$ that makes use of property Assumption 8 as follows:

$$V(s - G) = P(s) \tag{3.24}$$

Next, using Equation 3.24 we differentiate Equation 3.23 implicitly with respect to the assigned goal $G$:

$$R''(\dot{s}^*(D,G))\frac{d\dot{s}^*(D,G)}{dG} = -V''(D\dot{s}^*(D,G) - G)\left[\frac{Dd\dot{s}^*(D,G)}{dG} - 1\right] \tag{3.25}$$

Rearranging, Equation 3.25 yields:

$$\frac{d\dot{s}^*(D,G)}{dG} = \frac{V''(D\dot{s}^*(D,G) - G)}{R''(\dot{s}^*(D,G)) + DV''(D\dot{s}^*(D,G) - G)} \tag{3.26}$$

Replacing Equation 3.24 in Equation 3.23, we have that:

$$V'(D\dot{s}^*(D,G) - G) = -P'(D\dot{s}^*(D,G)) \tag{3.27}$$

Notice now that if $\dot{s}^*(D,G)$ is decremented by an arbitrarily small $h > 0$, it holds from Equation 3.27 that:

$$V'(D\dot{s}(D) - G - Dh) > -R'(\dot{s}(D) - h) \tag{3.28}$$

From Equation 3.28, we note $DV''(D\dot{s}^*(D) - G) < -R''(\dot{s}^*(D))$ and $DV''(D\dot{s}^*(D) - G) + R''(\dot{s}^*(D)) < 0$. This implies that iff $V''(D\dot{s}^*(D) - G) > 0$ (i.e. which occurs according to Assumption 7 when $D\dot{s}(D) - G < 0$), then $\frac{d\dot{s}^*(D,G)}{dG} > 0$ and $\frac{ds^*(D,G)}{dG} > 0$. This implies that if a worker is already able to accomplish the goal before the deadline, then increasing the goal will increase total performance (and average work pace). If, however $V''(D\dot{s}^*(D) - G) < 0$ (by Assumption 7 occurs when $D\dot{s}^*(D) - G > 0$) then $\frac{d\dot{s}^*(D,G)}{dG} < 0$ and $\frac{ds^*(D,G)}{dG} > 0$. In this case, if a worker is not able to accomplish the goal before the deadline, then increasing the goal will result in a decrease of total performance, proving the desired result. □

It is possible to formulate another hypothesis regarding the goal level–total individual performance relationship which is consistent with the report of Locke and Latham (1982), and indeed

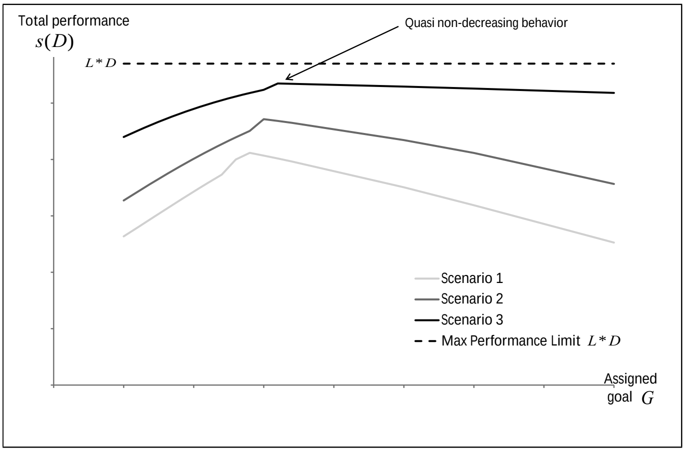



Figure 3.6: Goal level - total performance relationship for different scenarios

represents a majoritarian view on the field (Locke and Latham, 1990)(Locke and Latham, 1990), provided commitment towards the goal exists:

**Hypothesis 10** *The goal difficulty–total performance relation for a planner worker is strictly increasing with diminishing returns until converging to a threshold given by the limits of the worker's ability.*

**Theorem 10** *If for a planner worker it also holds that* $\max_G \dot{s}^*(D,G) \approx L$*, then* $\lim_{\dot{s}^*(D)\to L^-} \frac{ds^*(D,G)}{dG} = \lim_{\dot{s}^*(D)\to L^+} \frac{ds^*(D,G)}{dG} = 0$ *and* $\lim_{\dot{s}^*(D)\to L^-} \frac{d\dot{s}^*(D,G)}{dG} = \lim_{\dot{s}^*(D)\to L^+} \frac{ds^*(D,G)}{dG} = 0$.

**Proof** If we assume that $\max_G \dot{s}^*(D,G) \approx L$ may hold, then we may apply Assumption 3, $\lim_{\dot{s}\uparrow L^-} R''(\dot{s}) = -\infty$, and then it follows from Equation 3.26 that $\lim_{\dot{s}^*(D)\to L^-} \frac{d\dot{s}^*(D,G)}{dG} = \lim_{\dot{s}^*(D)\to L^+} \frac{d\dot{s}^*(D,G)}{dG} = 0$. □

This proof shows that for cases where workers are relatively insensitive to changes in their work pace, but at the same time it is extremely undesirable to work near the skill level $L$ (by Assumption 3), varying the goal may exhibit a quasi non-decreasing pattern, stabilizing at a threshold near the maximum skill level $L$ (see Figure 3.6). It is also important to observe that in this case, the planner model becomes more consistent with that of a constraint model, where performance is simply bounded by the skill level $L$.

### 3.6.3 Effects of varying skills on work pace regulation and total work

As in the previous sub-section, we simultaneously address the effects of skills on work pace regulation and total work by providing answers to the questions:"*What are the effects on work pace regulation if the skill level is increased under the influence of an assigned goal and deadline?*" (Question 6) and "*What are the effects on individual performance if the skill level increases under the influence of an assigned goal and deadline?*" (Question 2). For this we formulate the following intuitive hypothesis:

**Hypothesis 11** *If a planner worker has a higher skill level than another one, the time-invariant selected work pace of the worker with a higher skill level is higher than the worker with the lower skill.*

Hypothesis 11 may then be formalized with the following theorem:

**Theorem 11** *Given two myopic workers with skill levels $L_1$ and $L_2$ such that $L_2 = L_1 + \phi$ and $\phi > 0$, it holds that $\dot{s}^*_{L_2}(t) > \dot{s}^*_{L_1}(t)$ for $t \in [0, D]$ and $s^*_{L_2}(D) > s^*_{L_1}(D)$ . It also holds that $\hat{t}_{L_2} < \hat{t}_{L_1}$if $\hat{t}_{L_1}, \hat{t}_{L_2} \in [0, D]$.*

**Proof** The proof follows directly by using the same reasoning as in Step 1 of the proof of Theorem 4, where it holds that $g_{L_2}(x) > g_{L_1}(x)$ for $x \in \mathbb{R}$. Thus, it holds at $t = D$ that at $t = D$, that $g_{L_1}(P'(s(D))) > g_{L_1}(P'(s(D)))$ and thus, $\dot{s}_{L_2}(D) > \dot{s}_{L_1}(D)$ and $s_{L_2}(D) > s_{L_1}(D)$. $\square$

## 3.7 Overview and discussion

In this cha pter we have developed propositions regarding the possible effects of varying the goal level (difficulty) and skill level on performance and work pace regulation. Our framework starts by treating the worker as a decision maker himself who, in the tradition of the Behavioral Economics field, wishes to maximize his level of a desirability for a given effort level. The decision models we present here are parsimonious by including only a limited number of assumptions that are documented in the literature regarding work pace as a stressor and evaluation of performance. Table 3.1 summarizes the assumptions made in the building blocks of the models: the intrinsic and extrinsic evaluation and the support from the literature for them.

The propositions are derived under two different views on how the selection of work pace over time is made. In the first point of view, workers are said to be myopic because workers only consider the satisfaction obtained in the present to select their work pace. In the second point of view, workers are said to be planners because they consider the total satisfaction derived over the whole available period to reach the goal given an assigned deadline. Tables 3.2 (for total performance) and 3.3 (for work pace) provide a summary of the propositions presented in this chapter as possible answers to the research questions presented in Section 3.2. The propositions are compared to what is known in the existing literature.

Table 3.2: Goal difficulty-performance investigation overview

| | Evidence | |
|---|---|---|
| Questions and Answers | Literature | Decision model |
| *Question 1 What are the effects on individual performance (i.e. cumulative performance of an individual measured at the end of the assigned period) if the goal difficulty (level) increases?* | | |
| Possible answer 1 | | |
| The goal difficulty-total performance relation for a myopic worker is unimodal, increasing and then decreasing on the assigned goal level (Hypothesis 6 and Hypothesis 9). | Erez and Zidon (1984) | Theorem 6 (Myopic model)<br>Theorem 9 (Planner model) |
| Possible answer 2 | | |
| Total performance increases and then remains constant (levels off) with goal difficulty (Hypothesis 10). | Locke and Latham (1982 and 1990) | Theorem 10 (Planner model) |
| *Question 2 What are the effects on individual performance if the skill level increases under the influence of an assigned goal and deadline?* | | |
| Possible answer 1 | | |
| Performance (total work) increases given a skill increase (Hypothesis 7 (Myopic model) and Hypothesis 11(Planner model)). | Erez and Zidon (1984) | Theorem 7<br>Theorem 11 |
| *Question 3 What are the interaction effects of increasing goal difficulty (level) and skill level on individual performance?* | | |
| Possible answer 1 | | |
| Possible interactions may exist, although we do not make a-priori hypothesis. | Erez and Zidon (1984) | |

These comparisons highlight the advantage of formulating decision making models for theory building by linking different results on performance and work pace regulation within a single model. When the derived propositions are compared to reports in the literature, it can be observed that a myopic model may account for the reported acceleration towards the goal (Hull, 1932; See et al., 2006). In addition, it is seen that a goal level-performance relationship which levels-off can only be explained in the proposed framework with the additional assumption of an increase in the work pace over the natural work pace thereby resulting in only marginal decrements up to the proximity of the skill level. We also see that other propositions can be derived to which there is no documentation in the literature, in particular what happens if skills are varied in a goal-setting context. Furthermore, the results are organized by type of model, whereas a myopic model links the goal gradient hypothesis with a non-monotonic goal level-performance relationship, the planner model links a steady-state work pace regulation with a

Table 3.3: Work pace regulation investigation overview

| Questions and Answers | Evidence: Literature | Evidence: Decision model and justification |
|---|---|---|
| *Question 4 How is the work pace regulated under the influence of a given goal and deadline?* | | |
| Possible answer 1 | | |
| A worker will accelerate towards the goal, reaching its maximum work-pace when he reaches the goal and then decelerate converging to the natural work pace if enough time is allowed (Hypothesis 1). | Goal gradient hypothesis (Hull, 1932; See et al., 2006 and Kivetz et al., 2006) | Theorem 1 (Myopic model) |
| Possible answer 2 | | |
| A worker will set a time invariant work pace for the whole period (Hypothesis 8). | The alternative hypothesis, if there is no acceleration towards the goal. | Theorem 8 (Planner model) |
| *Question 5 What are the effects on work pace regulation if the goal difficulty (level) is increased?* | | |
| Possible answer 1 | | |
| The work pace selected is shifted for the whole period by a constant lapse in time (Hypothesis 2).<br>When a higher goal is assigned, workers will start working at a lower work pace (Hypothesis 3). | Goal gradient hypothesis (Hull, 1932; See et al., 2006 and Kivetz et al., 2006). | Theorem 2 (Myopic model)<br>Theorem 3 (Myopic model) |
| Possible answer 2 | | |
| If the goal increases, the constant work pace increases, otherwise it decreases (Hypothesis 9). | Consistent with Parkinson Law (1962) of work pace adjustment according to goal demands. | Theorem 9 (Planner model) |
| *Question 6 What are the effects on work pace regulation if the skill level is increased when a goal is assigned?* | | |
| Possible answer 1 | | |
| If a worker has a higher skill level than another one, the selected work pace of the worker with a higher skill level is higher as long as the goal has not yet been achieved (when the skill level is increased (Hypothesis 4).<br>The maximum observed work pace increases when the skill level is increased (Hypothesis 5). | The literature has not investigated this question. | Theorem 4 (Myopic model)<br>Theorem 5 (Myopic model) |
| Possible answer 2 | | |
| If a worker has a higher skill level than another one, the time-invariant selected work pace of the worker with a higher skill level is higher than the worker with the lower skill (Hypothesis 11). | The literature has not investigated this question. | Theorem 11 Planner model |
| *Question 7 What are the effects on work pace regulation when the skill level assigned goal interact?* | | |
| Possible answer 1 | | |
| Possible interactions may exist, although we do not make a-priori hypothesis. | The literature has not investigated this question. | |

non-monotonic relationship that may "appear" as a monotonic one if the maximum work pace chosen converges to that of the skill level limit.

Given that a priori it is not possible to know which of the propositions presented in this chapter are correct, the validity of the propositions and models are tested in Chapter 4. It is expected that more complex behavior is observed in the matter of work pace regulation over time than the one exposed in this chapter. In particular, work pace adjustment behavior may exist (or plan revision), where deviations from the ideal work pace trajectory and the actual work pace trajectory are minimized (Carver and Scheier, 1998). Nonetheless, the fact that the models proposed in this chapter, stylized with simple properties, allows for comparison of the basic features of the goal level-performance relationship and work pace regulation found in the experimental studies of Chapter 4.

Another potential value of the models presented in this chapter is that once one of the alternative views is validated, modelers and practitioners may have an additional tool to forecast possible work pace regulation of workers given different assigned goals, deadlines and skill level scenarios. Furthermore, the results may be aggregated to a number of heterogeneously skilled workers. The proposed models are also easily extended to include learning and fatigue effects as part of the utility rate work pace function, creating temporal shifts of maximum and most comfortable levels of capacity. In sum, all this information may be included in simulation studies of particular production systems or even decision support systems that consider assigned goals as a selection variable.

# Chapter 4

# Behavioral goal setting models for operations management: An empirical approach

## 4.1 Introduction

In Chapter 3, we stressed the need for studying the assignment of performance goals and deadlines from an operations management perspective. The potential productivity benefits associated with goal assignment (Locke and Latham, 1990) and the fact goal assignment is an additional variable at the disposal of production managers that is not considered in most operations management models (Boudreau et al., 2003), were cited as important reasons for studying goals from an operations management perspective.

In fact, questions remain from an operations management perspective that will be studied in this chapter. A primary question is whether the goal-level–performance relationship is non-monotonic or non-decreasing (converging to a certain threshold). This is a question that needs to be answered to be able to assign optimal goals in operational contexts. It is also necessary to validate previous results from the literature on the goal-level-performance relationship for operational contexts. In particular, we consider the common operational context in which workers are assigned to shifts and block times and thus are given a fixed deadline to achieve their goal, which they can also overachieve.

A second question is how the work pace is regulated while workers aim to achieve a goal. From a modeling perspective, operational models predominantly assume that workers process jobs at a steady state. It is then relevant to verify if this assumption is justified under the influence of goals. A proper characterization of work pace regulation is also important for managers who want to monitor the progress of their workers towards the goal and wish to estimate if these are attainable. This is particularly true given previous reports that workers accelerate towards a goal. This phenomenon, however, occurred in cases where workers could stop when they reached their goal. These contexts are different from the contexts studied in this chapter, where workers work for fixed periods. If workers can produce more than the goal, such extra productivity is desirable for managers and to a certain extent, the workers.

Finally, in studying the goal-level-performance relationship in conjunction with work pace regulation it is important to understand the effects of varying skill levels (i.e. maximum work capacity). In any group of people, individuals have different capabilities, some individuals have a greater capacity to perform than others (Doerr and Arreola-Risa, 2000). Studying the goal-level-performance relationship while discriminating results across skill levels permits us to further characterize the relationship and identify which features are governed by the skill level of an individual. Studying work pace regulation patterns while acknowledging varying skill levels, has the potential to reveal insights to the key question of whether the assigned goal really forces a worker to work to the best of his ability.

In this chapter, we test the hypotheses derived in Chapter 3 regarding the effects of varying goals and skills on performance and work pace regulation over time within an operations management context. These hypotheses are possible answers to the questions posited in Section 3.2 of this thesis and summarized in Tables 3.2 and 3.3. Chapter 3 provided alternative hypotheses by deriving two alternative decision making models. In the first model, the workers where assumed to behave in a myopic manner, selecting their work pace by considering only the instantaneous desirability of a given work pace. In the second model, the workers where assumed to behave as planners, selecting their work pace by considering the total desirability of the selected work pace accumulated until the assigned deadline. Determining which model is most consistent with empirical evidence, has in itself a theoretical value for goal setting theory and can serve as a first step in modeling goal setting behavior in workers.

For testing the hypotheses derived from our alternative decision making models of the worker, we conducted a controlled, repeated-measure lab experiment where difficulty levels were varied while performance as well as work pace regulation were observed. To the best of our knowledge, we are the first to directly test goal setting phenomena from the perspective of work pace regulation. Not only do we register total performance, but also the instants at which each job is completed. In addition, the experimental study allows for studying trade-offs between productivity and quality and assesses how performance is evaluated with respect to the goal (an indirect measure of frustration) with the purpose of evaluating the limitations of assigning goals in an operational context. Statistical tests are then used to accept/refute the hypotheses posited in Chapter 3, analyzing differences across and within individuals.

This chapter is organized as follows. Section 4.2, describes the method used for testing the aforementioned hypotheses in an experimental setting. We start presenting the results of our experiment in Section 4.3 where we attempt to shed light to the internal process that makes goals work; i.e. how goals fix expectations. Next, in Section 4.4, we report the results of the experiment on the total performance effects seen when varying goals and skills. Similarly, Section 4.5, reports the results of the experiment on the work pace regulation effects seen when varying goals and skills. In Section 5, we present the results regarding the internal process that makes goals work; i.e. how goals fix expectations. Section 6, presents results on limitations in assigning goals, namely, the trade-offs between performance gains and quality levels. Finally, we conclude this chapter by presenting a discussion of the key findings, limitations and implications for operations management of the study in Sections 7, 8 and 9 respectively.

## 4.2 Method

In this section we describe the methodology used for testing the hypothesis summarized in Tables 3.3 and 3.4 of Chapter 3 through a laboratory experiment. A laboratory based experiment is advantageous over a field study in that it controls goal difficulty in a precise manner where the influence of unsystematic variation is minimized. Unexpected breakdowns, distractions or interference between workers that are common in operational contexts are avoided.

### 4.2.1 Sample

The participants for the experiment were recruited from a participantpool of 1st and 2nd year bachelor students of business administration. For a pilot study undertaken to set the conditions of the experiment and check the effectiveness of feedback in the experiment, other, $n = 36$ students were recruited. A separate set of $n = 81$ students were recruited for the actual experiment. All participants received two course extra–credits regardless of their performance in the experiment. Although we acknowledge that differences may exist in simulating working conditions using students as compared to real workers, we note that goal setting experiments have in general replicated results from the laboratory in the field (Locke and Latham, 1990). Moreover, the designed experiment remains adequate for the purpose of our study which is to study the theorized effects of varying goal difficulty in performance as well as in work pace and not to arrive to conclusions regarding the size of effects which may vary across operational contexts (Highhouse, 2009).

### 4.2.2 Experiment design

The experiment conducted has a within-participants design. This means that participants in the experiment were exposed to all experimental conditions as opposed to a between-participants design where participants are assigned randomly to only one condition. The three conditions of the experiment consisted of three varying levels of goal difficulty.

We note here that because repeated measurements were taken to observe work pace regulation patterns, the probability of not observing consistent differences in such patterns across different goal conditions increases. For this reason, the experiment had to be designed to ensure the highest statistical power possible, avoiding individual differences to account for observed differences in response. Therefore, we selected a within-participants design that ensures that the source of the response variation is due to the different treatments (i.e. goal levels) and not due to individual differences across treatment groups as occurs with between-participants experiment designs (Kantowitz et al., 2008). In addition, the within-participants approach allows for direct comparisons of performance and work pace regulation for given individuals.

A within-participants design does have the drawback of the possibility of carry-over effects. In our case, those effects may be in the form of fatigue or additional adaptation of the worker's performance evaluation given past goals and performance (Mezias et al., 2002). To mitigate the influence of these effects on the results a number of actions were undertaken.

First, the sequence at which each goal difficulty level was presented was randomized to average out any goal-anchoring and fatigue effects. Importantly, this is an advantage over the Erez and Zidon (1984) goal difficulty–performance study, where participants were presented with increasing goal levels, allowing for the confounding of variables. Next, to minimize fatigue effects participants were allowed to rest and stretch for 1 minute after each picking round of 8 minutes. To avoid learning effects a supervised training round of 4 minutes was conducted first, where the experimenter verified that the exact procedure was followed by the participant. Finally, to ensure that sequence effects were not present, control variables indicating the sequence by which an assigned goal was introduced, were included in the subsequent statistical analysis.

### 4.2.3 Experimental task

Participants were asked to conduct a simple simulated order picking task. In the experiment, each participants was told to imagine himself as a worker in a warehouse. The task was simple enough to be learned quickly (in less than 4 minutes) and sufficiently short cycled enough (less than 12 seconds) for an individual to be able to observe progress towards the goal and judge his ability with respect to a goal. The experiment layout is shown in Figure 4.1. The simulated order picking task consisted of the following steps: (1) receiving instructions indicating the bin to pick from (Bin 1, 2 or 3), (2) walking to the corresponding bin, (3) retrieving a packaged stack of 200 post-its (acting as a product, 0.3 cm thick) from the corresponding bin, (4) walking back to the terminal, (5) typing the 4-digit number printed at both sides of the post-it (acting as the product code), (6) dropping the post-it stack in a drop-bin and (7) confirming the pick pressing enter at the terminal's keyboard. The correctness of a pick was evaluated by verifying whether the 4-digit number corresponded to that of the selected bin. The participants were advised that only correct picks were counted towards an assigned goal. Therefore, quality, although not a goal in itself, constrained the work pace as incorrect picks implied unproductive and undesirable time spent towards the goal. To minimize errors, participants were asked to use only the number pad of the key-board. Only keys that corresponded to digits were enabled.

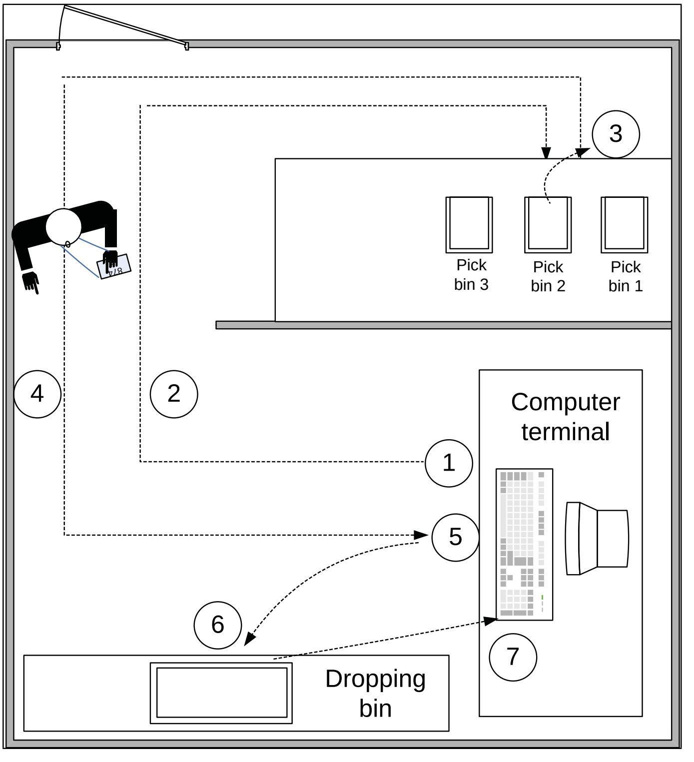



Figure 4.1: Experiment layout and order picking cycle

Feedback was constantly shown on the screen indicating the assigned goal, the time left remaining until the deadline and the number of picks accomplished (see Figure 4.2 for a screenshot of the interface shown to participants). The questions, instructions and interactive screens were all implemented using Macromedia Authoware 7$^{\mathrm{TM}}$. In a pilot study it was found that the visual feedback competes in attention with the instructions of which bin to pick as well as the 4-digit number. Hence, to assure that the participants were aware of their progress, computerized voice feedback was also given every 2 minutes indicating the number of picks achieved and the time left. The effectiveness of the auditory feedback was confirmed with a follow-up question regarding the participants' awareness of the feedback. When the goal was achieved, the bold letters on the screen changed color form black to green. In a posterior debriefing 86% of participants reported being aware when they were proximal to the goal. Follow-up questions in pilot studies showed that participants were aware of when they achieved their goal. Lastly, if the pick was incorrect, a message on the screen indicated this and the participant was asked to pick a new "product" (i.e. another post-it).

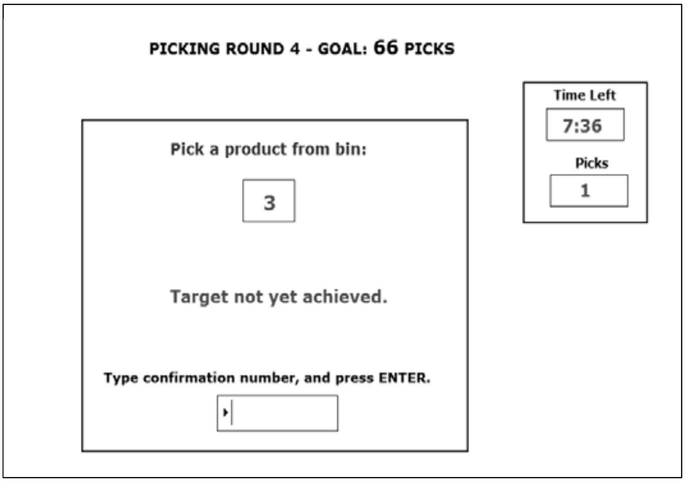



Figure 4.2: Screen-shot during picking rounds

Each participant was presented with three different picking rounds lasting 8 minutes each. The goal was stated as a number of picks that must be achieved within the time span of the round. Participants ($n = 81$) were requested to pick either 47, 59 or 66 products in 8 minutes. Each goal corresponds to a fixed percentage of participants in the pre-test that were told to "Do their best" ($n = 36$) and were able to achieve the goal. In this way for a goal of 47 picks, 90% of the pre-test participants were able to achieve it, whereas for a goal of 59 picks, 50% were able to achieve it and finally, for a goal of 66 picks, only 10% were able to achieve it. These percentages were fixed following the recommendation of Locke and Latham (1990) to observe significant differences in performance.

As stated in Chapter 3, our study assumes commitment to achieve the goal by assigning a realistic goal. Indeed, Locke and Latham (1990) have observed from several experiments that goal commitment is generally the case as long as goals remain realistic. In Erez and Zidon (1984), participants where committed towards the goal up to the point where only 10% of the population were able to attain it. This corresponds to our most difficult goal, fixed at the 90th percentile of ability.

However, to enhance commitment and realism, at the start of the experiment participants were told that they will be evaluated by comparing their actual performance to the actual goal, by a hypothetical boss. Moreover, they were told that repeatedly over-achieving (underachieving) the goal in a working setting will yield desirable (undesirable) consequences for their job such as paid bonuses, promotions, prizes (penalties, being fired). This ambiguous and long term link between achieving (underachieving) the goal and positive (negative) consequences is in fact quite realistic in jobs that do not apply piece-rate systems. In those jobs, it is consistency in (not-)achieving the goals assigned that is rewarded (punished), this avoids "speculation" of performance.

In addition, to measure the workers' skill level (or maximum capacity to perform, denoted by $L$ in Chapter 3) and most comfortable work pace level (denoted by $n$ in Chapter 3), two additional picking rounds were conducted. These picking rounds correspond to the second and third picking rounds presented to participants (before the three picking rounds with assigned goal difficulty). The second picking round asked participants to work at their most comfortable work pace (i.e. $n$) while the third picking round asked participants to work at their highest work pace possible (i.e. $L$).

### 4.2.4 Measurements

**Skill measurement**

In Chapter 3, we refer to the skill level $L$ as the maximum work pace an individual can achieve. We acknowledge that certain participants may not be willing to reach their maximum work pace for a brief period when told to do their best. Therefore, it is difficult to verify such willingness by only observing behavior. As a solution, we propose a proxy for the skill of participants by averaging the corresponding work pace of the 10 fastest cycle times performed in the "do your best" picking round. For the effect of subsequent analysis, we then identified four quartiles of performance, classifying the participants according to their skill level (i.e. Skill Level 1, 2, 3 and 4) such that skill Level 4 corresponds to the top 25 % of performers. The validity of this proxy was checked by the analysis itself, where the skill proxy was able to discriminate between patterns of work pace regulation and results of total performance.

**Performance measurement**

To measure production performance, the number of correct picks were tallied for each picking round. Furthermore, the work pace was measured by registering the time stamp at which a pick is confirmed (i.e. when the participant presses enter on the keyboard). The incorrect picks were also registered so as to tally the number of incorrect picks and be able to derive relative quality measures (i.e. number of correct picks over total number of picks).

**Performance evaluation measurement**

The extrinsic motivation was studied before every goal picking (47, 59 and 67 picks) round by asking workers to evaluate their level of satisfaction with their own performance for different hypothetical levels of performance by using a 0 to 100 scale rating (with a 10 point increment). The hypothetical levels of performance were 20, 40, 60, 80, 100 and 120% of the assigned goal. However, it must be noted that only absolute values of performance were given as opposed to relative values with respect to the goal to avoid any calculating behavior and repetition in the answers.

The purpose of this performance evaluation measurement is to validate an "S-shaped" utility function of performance as described in Chapter 3. For this reason, positive and negative evaluations were not discriminated when participants were asked to report their levels of satisfaction. If a positive and a negative scale of performance evaluation were offered, this may have resulted in a normalization of reported scores in both scales. For our purposes, a normalization of scores in both scales was undesirable as one of the key characteristics to validate the "S-shaped" utility–performance function (Kahneman and Tversky, 1979) is that of loss aversion, and this would not have been verifiable with a normalization of reported scores.

### 4.2.5 Statistical methods

To test the hypotheses provided in Tables 3.2 and 3.3 for answering the corresponding research questions, we conducted a series of statistical procedures. In this sub-section we detail the statistical procedures followed in our analysis of total performance (i.e. Questions 1, 2 and 3) and work pace regulation (i.e. Questions 4, 5, 6 and 7).

**Total performance analysis**

In this case, the dependent variable is total cumulative performance for a participant measured at the deadline, denoted in Chapter 3 as $s(D)$. To compare total individual performance across experimental conditions (i.e. goal levels) an ANOVA repeated measures test was used because each participant was exposed to all three experimental conditions, making the three samples for each experimental condition related (Field, 2005). Furthermore, to explore the differences between particular experimental conditions, contrasts were preferred as opposed to repeated pairwise t-tests so as to avoid inflation of the total error when repeatedly comparing means (Field, 2005).

**Work pace analysis**

As the dependent variable is the work pace over time, we first describe how this measure is derived from the data obtained. First, the cycle-time for each pick was calculated by subtracting the time stamp at which the pick was started from the time stamp at which the pick was completed. Note that the corresponding starting time stamp is either the time stamp of the previous completed pick or the time stamp of the start of the picking round. Each cycle time corresponding to a correct pick was then inverted to calculate the corresponding work pace for each pick. Next, the work pace results of the 8 minute-period picking rounds where divided in 16 intervals of 30 seconds each. The work pace for each completed pick was assigned to the corresponding time interval in which the pick was completed. Finally, all the work paces corresponding to each interval were averaged, obtaining an average for the work pace.

Discretizing time into 16 intervals enabled comparison of work pace regulation across participants and also serves the purpose of smoothing out irregularities in performance, allowing for an easier identification of trends in work pace regulation. Moreover, by calculating the average work pace of completed picks per interval, the first and last time interval work pace measures were not affected by incomplete picks.

Although only correct picks were considered for evaluating the total performance, for the purpose of work pace analysis, the incorrect picks were also tallied and considered within each interval of analysis. The reason for this procedure is that the intervals contain on average very few picks (i.e. only 2.5 – 5 picks per time interval) and considering the time spent in a wrong pick as unproductive distorts the work pace regulation trends which we are interested in analyzing.

To analyze work pace regulation over time, given certain goals and certain skills, we conducted a linear model analysis. Given the experiment design, the data available has a structure where a pick is embedded within a picking round which in turn is embedded within a participant that executes the picks. This structure implies that the independence of violations is violated by construction of the experiment, where observations in a single picking round for a given participant are more related to each other than observations from different picking rounds and different participants. For this reason, the analysis should not be done using an Ordinary Least Squares (OLS) procedure, as such a procedure assumes independence of observations.

To solve the problem of dependency of observations in a given structure, we conducted a Multilevel Linear Model (MLM) also referred to as Hierarchical Linear Model (HLM), (Gelman and Hill, 2007) where the structure of the data can be modeled explicitly such that the intercept and slope of time are allowed to vary according to the picking round and participant. Moreover, the effect of the goal level assigned and skill level of the participant were modeled at the corresponding level of analysis; the former at the picking round level (Level 2) and the latter at the participant level (Level 3).

We then structure, the nested model as follows, where 15 observations, $k = 0, 1, ..., 14$, of the 30-second intervals are nested within a picking round $j = 1, 2, 3$ and a picking round is nested within a participant $i = 1, 2, .., 81$. It is important to note here that observations of the last time interval (i.e. $450 - 480$ seconds) are dropped from the analysis as Figure 4.7 suggests a break in trend that we further discuss in analyzing Question 4. With this structure, we introduce the following notation for variables and indices:

Additional indexes

$m_j$ : Index variable indicating goal assigned at picking round $j$.
If $m_j = 1$, the goal is 47 picks, if $m_j = 2$, the goal is 59 picks, if $m_j = 3$, the goal is 66 picks.

$n_i$ : Index variable indicating skill level of participant $i$.
The number $n_i = 1, 2, 3, 4$ indicates the skill level where $n_i = 4$, implies that participant $i$ belongs to
the top 25% of performers and $n_i = 1$, implies that participant $i$ belongs to the bottom 25%.

Dependent variable

$\dot{s}_{i,j,k}$ : Average work pace in picks/minute at the $k$th interval in the $j$th round executed by participant $i$.

Control variables

$H_{i,j}$ Dummy variable that equals 1 if participant $i$ executing a goal in picking round $j$ has executed in a
previous picking round a goal of 66 picks (i.e. $m_{j-1} = 3$ or $m_{j-2} = 3$); 0 otherwise.

$SQ_{i,j}^{(o)}$ Dummy variable indicating the picking round sequence. If the picking round $j$ of picker $i$, equals $o$
then the variable equals 1; 0 otherwise. Note that $o = 1, 2$ ($o = 3$ is the default).

Independent variables

$t_{i,j,k}$ Time instant in minutes at which the average work pace of participant $i$ was measured for the
$j$th round at the end of $k$th measurement interval.

$G_{i,j}^{(m)}$ : Dummy variable that equals 1 if goal $m$ is assigned to the $j$th round to the $i$th participant and 0
otherwise. Note that $m = 1, 2$ ($m = 3$ is the default).

$L_i^{(n)}$ : Dummy variable that equals 1 if skill level $n$ is assigned to the $i$th participant and 0
otherwise. Note that $n = 2, 3, 4$ ($n = 1$ is the default).

The parameters and error terms to be estimated are described as follows:

Estimation parameters

$\beta_{a,i,j}$ : Parameter to be estimated for the $j$th round picked by the $i$th participant; $a = 0$ refers to intercept estimate, $a = 1$ refers to slope intercept.

$\delta_{b,m,i}$ : Parameter to be estimated for the $i$th participant (if applicable) when goal $m$ is assigned (if $m > 0$); $b = 0$ refers to intercept estimate, $b = 1$ refers to slope intercept.

$\eta_o$ : Parameter for control variables, $n = 1$ is associated to the first picking round, $n = 2$ to the second picking round and $n = 3$ to the dummy variable $H_{i,j}$.

$\gamma_{c,m,n}$ : Parameter to be estimated for assigned goal $m$ and participant of skill level $n$; $c = 0$ refers to intercept estimate, $c = 1$ refers to slope intercept.

Error terms

$e_{i,j,k}$ : Random term in the model associated with the $k$th interval in the $j$th round picked by participant $i$.

$u_{0,i,j}$ : Random term associated with the intercept of the model that depends on the $j$th picking round and the $i$th participant.

$u_{1,i,j}$ : Random term associated with the slope of the model (time) that depends on the $j$th picking round and the $i$th participant.

$v_{0,0,j}$ : Random term associated with the intercept of the model that depends on the $j$th participant.

$v_{1,0,j}$ : Random term associated with the slope of the model that depends on the $j$th participant when goal $m = 1$ is assigned.

$v_{1,1,j}$ : Random term associated with the slope of the model (time) that depends on the $j$th participant when goal $m = 2$ is assigned.

$v_{1,2,j}$ : Random term associated with the slope of the model (time) that depends on the $j$th participant when goal $m = 3$ is assigned.

Hence, we define the hierarchical model as follows:

Level 0: Picking interval $k$

$\dot{s}_{i,j,k}=\quad \beta_{0,i,j}+\beta_{1,i,j}t_{i,j,k}+e_{i,j,k}$

Level 1: Picking round $j$

$\beta_{0,i,j}=\quad \delta_{0,0,i}+\delta_{0,1}G_{i,,j}^{(1)}+\delta_{0,2}G_{i,,j}^{(2)}+\eta_1 SQ_{i,j}^{(1)}+\eta_2 SQ_{i,j}^{(2)}+\eta_3 H_{i,j}+u_{0,i,j}$

$\beta_{1,i,j}=\quad \delta_{1,0,i}+\delta_{1,1,i}G_{i,,j}^{(1)}+\delta_{1,2,i}G_{i,,j}^{(2)}+u_{1,i,j}$

Level 2: Participant $i$

$\delta_{0,0,i}=\quad \gamma_{0,0,0}+\gamma_{0,0,1}L_i^{(2)}+\gamma_{0,0,2}L_i^{(3)}+\gamma_{0,0,3}L_i^{(4)}+v_{0,0,i}$

$\delta_{1,0,i}=\quad \gamma_{1,0,0}+\gamma_{1,0,1}L_i^{(2)}+\gamma_{1,0,2}L_i^{(3)}+\gamma_{1,0,3}L_i^{(4)}+v_{1,0,i}$

$\delta_{1,1,i}=\quad \gamma_{1,1,0}+\gamma_{1,1,1}L_i^{(2)}+\gamma_{1,1,2}L_i^{(3)}+\gamma_{1,1,3}L_i^{(4)}+v_{1,1,i}$

$\delta_{1,2,i}=\quad \gamma_{1,2,0}+\gamma_{1,2,1}L_i^{(2)}+\gamma_{1,2,2}L_i^{(3)}+\gamma_{1,2,2}L_i^{(4)}+v_{1,2,i}$

The model can then be summarized in one level, as follows, showing the fixed intercept and slope effects as well as the random effects of the model:

$$\begin{aligned}\dot{s}_{i,j,k}= & \left(\gamma_{0,0,0}+\sum_{m=1}^{2}\delta_{0,m}G_{i,j}^{(m)}+\sum_{o=1}^{2}\eta_o SQ_{i,j}^{(o)}+\eta_{3,j}H_{i,j}+\sum_{n=2}^{4}\gamma_{0,0,(n-1)}L_i^{(n)}\right)\\ & +\left(\gamma_{1,0,0}+\sum_{m=1}^{2}\gamma_{1,m,0}G_{i,j}^{(m)}+\sum_{n=2}^{4}\gamma_{1,0,(n-1)}L_i^{(n)}\right.\\ & \left.+\sum_{n=2}^{4}\sum_{m=1}^{2}\gamma_{1,m,(n-1)}L_i^{(n)}G_{i,j}^{(m)}\right)t_{i,j,k}\\ & +u_{0,i,j}+v_{0,0,i}+(u_{1,i,j}+\sum_{m=1}^{2}v_{1,m,i})t_{i,j,k}+e_{i,j,k}\end{aligned}$$

The model allows us to evaluate the selection of the initial work pace and its determinants (i.e. goal level, skill levels and/or an interaction of both) as well as determinants of a linear tendency in work pace regulation (i.e. goal level, skill levels and/or an interaction of both). In addition, to control for carry-over effects, a number of variables were introduced. First, to account for fatigue, the dummy variables $SQ_{i,j}^{(1)}$ and $SQ_{i,j}^{(2)}$ indicated the sequence by which the picking round was presented to the picker ($o=3$ was taken as the reference value). The variable $H_{i,j}$ was used to see the impact of being exposed to the most difficult goal earlier (i.e. 66 picks).

## 4.3 Performance evaluation

In Chapter 3, an S-shaped utility performance function, $P(s)$, was proposed as a way by which workers evaluate their individual performance given an external goal. The proposed function shared characteristics common to prospect theory utility curves (Kahneman and Tversky, 1979). The empirical results shown in Figure 4.3 provides evidence that supports all the main characteristics proposed of a typical prospect theory curve: 1) the goal serves as a reference point, 2) loss aversion and 3) diminishing sensitivity.

The first property can be verified indirectly as it can be seen that a maximum increase in satisfaction with performance occurs for performance levels that are proximate to the assigned goal and also proximate to the point where the concavity of the curve changes. The second property can be verified by comparing the available score ranges above and below the inflection point where the goal is attained that serves as a reference point. The negative ranges (below the satisfaction level obtained at a performance level matching the goal) are 4-times larger than the

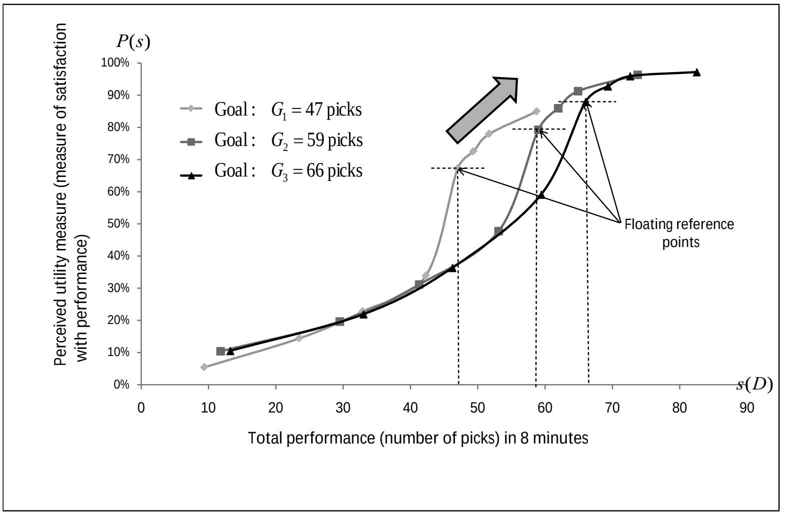



Figure 4.3: Empirical "S-shaped" performance evaluation curve across goals

positive ones (above the satisfaction level obtained at a performance level matching the goal - see Figure 4.3), thus providing evidence for loss aversion. The third property is also easily verified by noting a decrease in the gradient of the curve shown in Figure 4.3 when the performance level is more distant to the assigned goal.

We note, however, that the curve in Figure 4.3 "flattens" only for performance levels larger than the goal assigned, whereas for performance levels lower than the goal assigned the gradient of the curve does not flatten completely. This suggests that if a myopic model is applied, as studied in Chapter 3, an acceleration towards the goal should occur almost from the start of the activity. As the results show that no such acceleration occurs, this is an additional argument to support the planning model over the myopic model where any acceleration effects towards the goal are smoothed out. In addition, this effect, contradicts earlier reports of acceleration towards the goal (e.g. See et al., 2006) where the acceleration is only observed in proximity of the goal, but not from the start of the activity.

Furthermore, we also have support for the assumption of our model that the "S-curve" shifts to the right when the goal is increased. However, the effect is more complex than hypothesized a priori as not only a shift to the right along the horizontal axis exists, but the reference point also varies (i.e. "floats") across goal conditions. Figure 4.3 shows that the desirability obtained at different goals, i.e. reference points, actually increases, from this we may infer what is common wisdom: achieving more challenging goals provides higher levels of motivation. In this way, an effect not reported in the valuation curve of prospect theory (Kahneman and Tversky, 1979) is found: the reference points may vary in predictable ways across different contexts, in this case,

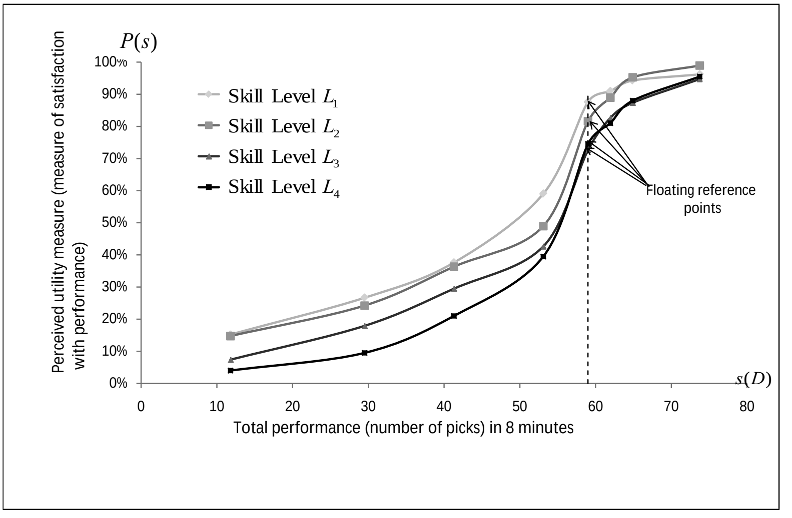



Figure 4.4: Empirical “S-shaped” performance evaluation curve across skill levels

the goals assigned. Thus, although different reference points exist for different contexts (i.e. goals assigned), these may also be compared one against each other *across* contexts.

In addition to this, Figure 4.4 shows how the “S-curve” varies with the skill levels of individuals. The S-shaped function that evaluates performance in the presence of a goal is robust to variations is skill; the main characteristics of the curve are maintained. Interestingly, Figure 4.4 shows a minor effect from increasing the skill levels, similar to that of increasing the goal levels, however the effect is smaller. The “S-curve” shifts slightly to the right, implying that more skilled individuals require higher levels of performance for the same level of satisfaction with their performance.

## 4.4 Total performance results

The results concerning total performance at the end of a picking round as the dependent variable are presented under the headlines of three research questions as shown in Table 4.5, where the empirical evidence is contrasted with both support from literature as well as the myopic and planning decision making models presented in Chapter 3. We organize the results of Table 4.5 under the headings of each of the posited questions, testing first the effects of varying goals, then skills and finally the interaction of the two.

**Question 1** *What are the effects on individual performance (i.e. cumulative performance of an individual measured at the end of the assigned period) if the goal difficulty (level) increases?*

Using the entire sample collected, the results show consistency with Locke and Latham (1990) by indicating a linear effect (see Table 2) between goal difficulty and performance using a repeated measures ANOVA contrast test ($F(1,80) = 71.44, p < 0.01$). Note that this test fits our case where we have repeated measures of the same variable (i.e. total performance) for each participant under each of the three experimental conditions and wish to test if performance increases linearly with the goal level assigned (Field, 2005). Further contrasts of performance between goal levels confirmed that a goal of 66 picks yields higher performance than a goal of 59 picks, ($F(1,80) = 12.85, p < 0.01$) and a goal of 59 picks yields higher performance than a goal of 47 picks ($F(1,80) = 53.19$, $p < 0.01$) (see Table 4.1).

Table 4.1: Total performance results across goal levels

| Assigned goal No. of picks | Performance No. of picks | Standard Error No. of picks |
|---|---|---|
| 47 | 59.68 | 0.80 |
| 59 | 64.37 | 0.83 |
| 66 | 66.62 | 0.98 |

The effectiveness of concrete goals is highlighted by comparing the experiment results, where explicit goals are assigned, to the pre-test results, where participants are urged to "do their best". In the pre-test, only 10% of participants obtained 66 picks or more whereas in the actual experiment when a goal of precisely 66 picks was assigned, 62% were able to obtain the goal (see Figure 4.5). It, therefore, is possible that the highest goal assigned (66 picks) is not challenging enough to observe a leveling-off or deterioration of performance.

To test whether performance is first increasing and then decreasing (as stated by Hypotheses 6 and 9 of the myopic and planner model, respectively) or non-decreasing (as stated Hypothesis 10 of the planner model) a repeated measures ANOVA was applied to the lowest skilled quartile of participants (i.e. Skill level 1), where the higher assigned goals are likely to be challenging. Applying such a procedure it was found that there is no deterioration of performance (in the number of picks) when the goal is raised from 59 picks ($M = 57.42$, $SE = 1.262$) to 66 picks ($M = 57.86$, $SE = 1.364$), ($p > 0.1$); whereas a significant difference does exist when the goal is raised from 47 picks to 59 picks ($F(1,77) = 7.438$, $p < 0.01$). Note further in Figure 4.6 that the average performance of pickers of Skill Level 1, was already insufficient for the goal of 59 picks and even more so when the goal is higher at 66 picks. This means that participants were already unable to achieve the goal; thus when the goal is further increased, the performance did not decrease. This provides support for Locke and Latham's (1982) finding of performance leveling off when the limits of ability are reached as well as Hypothesis 10 of the planner model. This result also provides indirect evidence that individuals are relatively insensitive to varying work pace up until close to the limits of skill. In the modeling framework of Chapter 3, this will

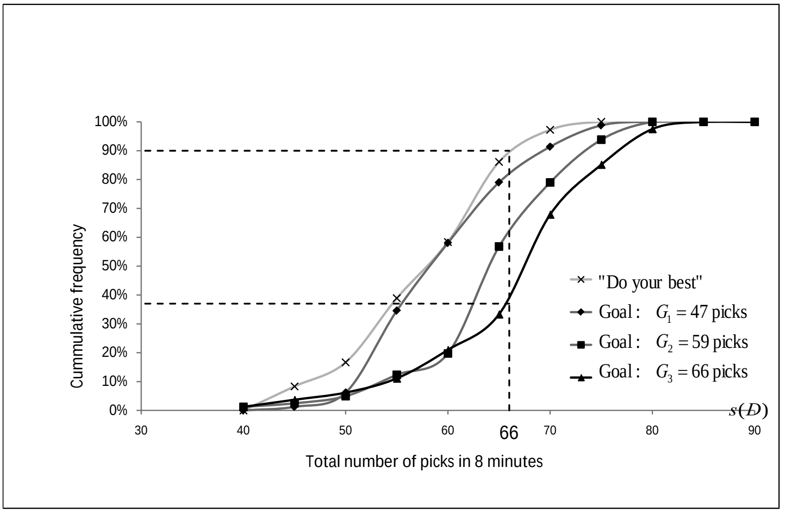



Figure 4.5: Cumulative distribution of participants performance across goals assigned

mean a work pace utility function (i.e. $R(\dot{s})$) that is relatively “flat” up until the skill level is reached.

Having established the effects of varying goals on performance, we do the same for varying skill levels as follows:

**Question 2** *What are the effects on individual performance if the skill level increases under the influence of an assigned goal and deadline?*

The answer to this question is almost tautological as skill level is defined by performance itself. However, the main effect is clear, indicating that the proxy for skill, based on a previous round where participants were asked to “do their best”, is in fact adequate: Pair-wise comparisons between skill levels confirm that higher skill levels exhibit higher performance (see Figure 4.4) tested with an ANOVA ($F(1, 80) = 90.43$, $p < 0.01$). All of the pair-wise comparisons are significant except when comparing Skill Level 2 with Skill Level 3, $t(80) = 0.545$. This indicates that the performance in the 2nd and 3rd quartiles are similar, implying certain concentration of performance towards the mean.

Finally, we test whether an interaction exists between varying skill levels and goal difficulties:

**Question 3** *What are the interaction effects of increasing goal difficulty (level) and skill level on individual performance?*

Further analyzing the effect of worker and performance across skill levels using a 2-way (required for interactions) repeated measure ANOVA we observe an interaction effect between

Table 4.2: Total performance results across skill levels

| Skill Level | Mean Performance No. of picks | Standard Error No. of picks |
|---|---|---|
| Skill Level 1 | 56.43 | 0.97 |
| Skill Level 2 | 62.90 | 0.80 |
| Skill Level 3 | 64.48 | 0.75 |
| Skill Level 4 | 70.77 | 0.84 |

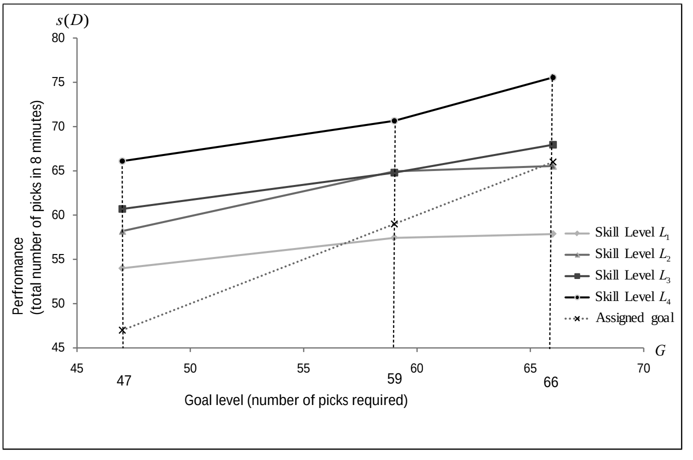



Figure 4.6: Total performance: goals and skill levels interaction

skill level and performance ($F(5.33, 136.84) = 2.11$, $p = 0.064$) as well as the expected main effect of skill level ($F(3, 77) = 31.63$, $p < 0.001$) as shown in Figure 4.6. This interaction effect is confirmed by observing the following. For the two highest quartiles (i.e. the 50% most skilled participants) there is an increase in performance ($M = 4.03$, $SE = 0.780$) when the goal is raised from 59 to 66 picks that is significant ($t(80) = 5.167$, $p < 0.001$). However, for the two lowest quartiles (i.e. the 50% least skilled participants), when the goal is raised from 59 to 66 picks, such an increase in performance ($M = 1.05$, $SE = 0.790$) is only moderate ($t(80) = 5.167$, $p = 0.091$). Thus, the increase in performance at the two highest quartiles is significantly higher than that at the two lowest quartiles ($t(80) = 2.975$, $p < 0.01$). This result provides further confirmation for Hypothesis 10, where increasing the goal yields an increase in performance when the maximum capacity to perform has not yet reached (as shown here for the 50% most skilled participants), but remains approximately constant when the maximum capacity has been achieved (as shown here for the 50% least skilled participants).

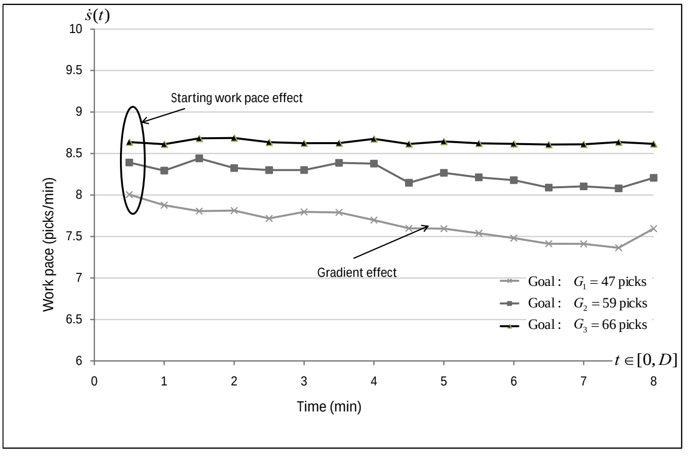



Figure 4.7: Average work pace regulation over time across goals assigned

## 4.5 Work pace results

Similar to the previous section, the results concerning work pace regulation as the dependent variable are presented under the headlines of the four research questions as shown in Table 4.6. In Table 4.6, the empirical evidence is contrasted with support from the literature and the myopic and planning decision making models presented in Chapter 3.

To answer these research questions, we use the results from the HLM analysis shown in Table 4.3. This analysis was conducted using the lme4 package (Bates and Sarkar, 2006) in the open source statistical software of R. For convenience in interpreting the results, it is important to note that the HLM model takes as reference values when the goal level $m = 3$ (i.e. 66 picks) is assigned and the Skill Level is $n = 1$ for convenience in interpreting the results. Note also that the control factors (i.e. $SQ_{i,j}^{(1)}$, $SQ_{i,j}^{(2)}$ and $H_{i,j}$) shown in Table 4.3 appear to be non-significant ($p > 0.1$) implying that there are no significant effects present in the experiment as a result of fatigue or adaptation towards the goal.

For effects of comparisons, we also include the OLS results (including only the fixed effects of the HLM analysis). However, only the HLM results are used for the analysis, as the others are deemed to have unreliable standard errors (Gelman and Hill, 2007). The work pace regulation patterns (across goals) are also illustrated in Figure 4.7, showing the average work pace for the 16 intervals measured for the 81 participants in the study.

Before analyzing the results of the model itself, we first note that the model does explain the variance in the data beyond the variation attributed to picking rounds and participants in the experiment. This is evidenced by contrasting the HLM Complete model with a constrained reference model that only includes an intercept and random effects; the model forces the parameters of all the explanatory variables equal to zero. Comparing both models (Table 4.3),

Table 4.3: HLM model estimation and fit analysis

*1. Fixed effects estimation*

| Fixed Effects Factors | | OLS Model Coeff | OLS Model S.E. | HLM Complete model Coeff | HLM Complete model S.E. |
|---|---|---|---|---|---|
| Intercept | $\gamma_{0,0,0}$ | 7.7827 | 0.0724*** | 7.7371 | 0.1647*** |
| Indicator variable - Goal presented 1st | $\eta_1$ | 0.0135 | 0.0369 | 0.0145 | 0.0836 |
| Indicator variable - Goal presented 2nd | $\eta_2$ | -0.0487 | 0.0362 | -0.0440 | 0.0823 |
| Indicator variable - Goal of 66 picks presented first | $\eta_3$ | 0.1818 | 0.0295*** | 0.1499 | 0.1356 |
| Time | $\gamma_{1,0,0}$ | 0.0146 | 0.0185 | 0.0092 | 0.0202 |
| Goal Level 47 Picks | $\gamma_{1,1,0}$ | -0.6913 | 0.0684*** | -0.6675 | 0.0917*** |
| Goal Level 59 Picks | $\gamma_{1,2,0}$ | -0.2346 | 0.0680*** | -0.2257 | 0.0899* |
| Skill Level 2 | $\gamma_{0,0,1}$ | 0.6147 | 0.0782*** | 0.6589 | 0.1982** |
| Skill Level 3 | $\gamma_{0,0,2}$ | 0.9799 | 0.0784*** | 1.0068 | 0.1972*** |
| Skill Level 4 | $\gamma_{0,0,3}$ | 1.6701 | 0.0781*** | 1.7067 | 0.1969*** |
| Time x Goal Level 47 Picks | $\delta_{1,1}$ | -0.0342 | 0.0222 | -0.0832 | 0.0287** |
| Time x Goal Level 59 Picks | $\delta_{1,2}$ | -0.0243 | 0.0221 | -0.0231 | 0.0243 |
| Time x Skill Level 2 | $\gamma_{1,0,1}$ | 0.0030 | 0.0237 | -0.0083 | 0.0285 |
| Time x Skill Level 3 | $\gamma_{1,0,2}$ | -0.0007 | 0.0237 | -0.0205 | 0.0284 |
| Time x Skill Level 4 | $\gamma_{1,0,3}$ | 0.0377 | 0.0237 | -0.0133 | 0.0284 |
| Time x Goal Level 47 Picks x Skill Level 2 | $\gamma_{1,1,1}$ | -0.0438 | 0.0246† | -0.0080 | 0.0402 |
| Time x Goal Level 47 Picks x Skill Level 3 | $\gamma_{1,1,2}$ | -0.0359 | 0.0245 | 0.0044 | 0.0402 |
| Time x Goal Level 47 Picks x Skill Level 4 | $\gamma_{1,1,3}$ | -0.1033 | 0.0245*** | 0.0049 | 0.0402 |
| Time x Goal Level 59 Picks x Skill Level 2 | $\gamma_{1,2,1}$ | 0.0446 | 0.0246† | 0.0156 | 0.0337 |
| Time x Goal Level 59 Picks x Skill Level 3 | $\gamma_{1,2,2}$ | -0.0161 | 0.0246 | -0.0202 | 0.0336 |
| Time x Goal Level 59 Picks x Skill Level 4 | $\gamma_{1,2,3}$ | -0.0885 | 0.0244*** | -0.0670 | 0.0336† |

*2. Random effects estimation*

| Random Effects Factors | | Constrained reference model Est. | Constrained reference model S.D. | HLM Complete model Est. | HLM Complete model S.D. |
|---|---|---|---|---|---|
| Level 0 Residual | $\sigma^2_{e_{i,j,k}}$ | 0.29484 | 0.54299 | 0.24212 | 0.49206 |
| Level 1 Pick round $j$ within participant $i$: Intercept | $\sigma^2_{u_{0,i,j}}$ | 0.50130 | 0.70802 | 0.26711 | 0.514866 |
| Level 1 Pick round $j$ within participant $i$: Time (slope) | $\sigma^2_{u_{1,i,j}}$ | | | 0.00342 | 0.05869 |
| Level 2 Participant: Intercept | $\sigma^2_{v_{0,0,i}}$ | 0.50214 | 0.70862 | 0.28820 | 0.53127 |
| Level 2 Participant: Time (slope) | $\sigma^2_{v_{1,0,i}}$ | | | 0.00227 | 0.04794 |
| Level 2 Participant: Time x Goal Level 47 Picks (slope) | $\sigma^2_{v_{1,1,i}}$ | | | 0.00547 | 0.00741 |
| Level 2 Participant: Time x Goal Level 59 Picks (slope) | $\sigma^2_{v_{1,2,i}}$ | | | 0.00055 | 0.02081 |
| Covariance Level 1 (Intercept-slope) | $\sigma_{(u_{0,i,j},u_{1,i,j})}$ | | | -0.30100 | |
| Covariance Level 2 (Intercept-slope) | $\sigma_{(v_{0,0,i},v_{1,0,i})}$ | | | -0.25200 | |
| Covariance Level 2 (Interaction terms) | $\sigma_{(v_{1,1,i},v_{1,2,i})}$ | | | 0.57600 | |
| Interclass Correlation Coefficient (ICC) Picking round level | | 0.3861 | | 0.3312 | |
| Interclass Correlation Coefficient (ICC) Individual level | | 0.3868 | | 0.3510 | |

*3. HLM Complete model fit evaluation*

| Criteria | Constrained reference model | HLM Complete model |
|---|---|---|
| Akaike Information Criterion (AIC) | 6782 | 6351 |
| $R^2$ Level 0 Increment | | 17.88% |
| $R^2$ Level 1 Increment | | 49.67% |
| $R^2$ Level 2 Increment | | 43.13% |
| $\Delta\chi^2$ ($\Delta$df=27) | | 579.17*** |

For HLM and OLS analysis, $n = 3631$.
In addition, for HLM, the following number of observations were observed per level:
time intervals per round= 15, rounds= 3, participants= 81
Significance levels: $p \leq 0.1$(†), $p \leq 0.01$(**), $p \leq 0.001$(***)
The HLM reference model includes only random effects for picking round and participant.

the Akaike Information Criteria (AIC) is lower for the HLM Complete model than for the constrained reference model, indicating a better fit of the HLM Complete model. Furthermore, a chi-squared ($\chi^2$) test to compare the change in the -2 log likelihood function (i.e. the function to be minimized in both models) relative to the additional degrees of freedom, confirms a better fit of the data by the HLM Complete model than the constrained reference model. Moreover, Table 4.3 shows that for each level analyzed the pseudo-$R^2$ (Kreft and Leuw, 1998), shows an improvement of the fit due to the additional variables of the HLM Complete model.

**Question 4** *How is the work pace regulated under the influence of a given goal and deadline?*

A first glance at the results shown in Figure 4.7, suggest that no acceleration towards the goal exists, only towards the deadline and thus does not support Hypothesis 1. However, it is possible that averaging across individuals may mask acceleration effects towards the goal, particularly taking into account that individuals with different skill levels reach their goals at different times. Hence, the data was analyzed from the point of view of progress by constructing intervals based on a constant length of about 5% in terms of progress towards the goal as opposed to time.

To construct these intervals, take for example the case of 59 picks as a goal. Every 2.95 picks, rounded to the nearest integral number of picks, the time lapsed is measured and then the corresponding work pace is calculated for that same interval. The exact time between each unit was measured and then the work pace was calculated knowing the number of picks between intervals. We then compared the average work pace of the $95-100\%$ progress interval with prior progress intervals (i.e. $75-80\%$, $80-85\%$) and a posterior progress interval ($100-105\%$) by conducting successive related sample paired t-tests. To avoid confounding acceleration towards the deadline, only participants that reached 105% of progress towards the goal, before the deadline where included in the analysis. None of the t-tests provided evidence for significant acceleration towards the goal or significant deceleration away from the goal ($p > 0.10$). As a result, we may then reject Hypothesis 1 derived from the myopic model.

On the other hand, from Figure 4.7, there does appear to be certain acceleration toward the deadline for the two lowest goals (i.e. 47 and 59 picks) where in the case of a goal of 47 picks, the work pace in the interval $450-480$ seconds is higher in picks/minute ($M = 7.62$, $SE = 1.17$) than that of the work pace in the interval 420-450 seconds ($M = 7.41$, $SE = 1.15$), ($t(80) = 3.17$, $p < 0.01$) and in the case of 59 picks, work pace in the interval $450-480$ seconds is higher ($M = 8.09$, $SE = 1.00$) than that of the work pace in the interval $420-450$ seconds ($M = 8.21$, $SE = 1.02$), ($t(80) = 3.167$, $p = 0.051$). Such a difference does not exist however, for the highest goal of 66 picks where the work pace for the interval $450-480$ seconds ($M = 8.64$, $SE = 1.13$) is non-significant with that of the work pace for the interval $420-450$ seconds ($M = 8.62$, $SE = 1.09$). A probable explanation for such acceleration towards the deadline for the highest goal may be that the participants may already be working at the limit of their ability (skill). More importantly, it is possible that the acceleration previously reported as acceleration

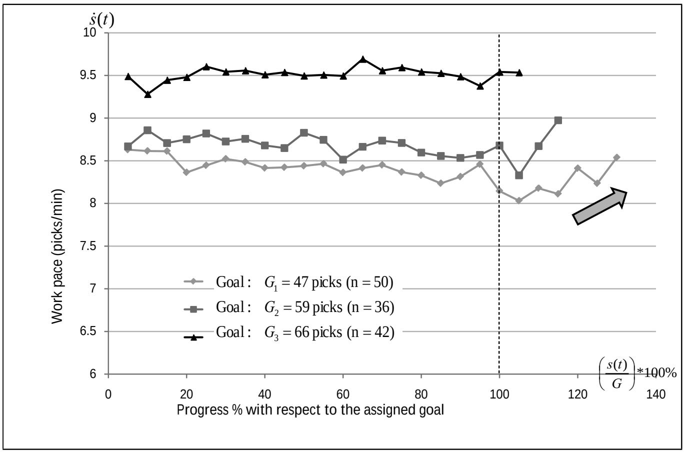



Figure 4.8: Average work pace regulation over progress towards the goal across goals assigned

towards the assigned goal (Kivetz, 2006 and See et al., 2006), may have been confused with acceleration towards the deadline where the end of the task was achieved when the assigned goal was achieved.

To illustrate this, consider Figure 4.8, that shows how the work pace is regulated over progress towards the goal. To avoid biasing the work pace average, the sample for each assigned goal was reduced to the workers achieving at least a certain level of performance (i.e. the maximum point for each series in the figure). Figure 4.8 shows that the acceleration occurs only after the goal is achieved and not before (i.e. after 100% of progress), confirming an acceleration towards the deadline and not towards the assigned goal.

In addition, from the HLM analysis there appears to be no main effects with respect to time ($p > 0.1$). This suggests that workers work at a steady state when a challenging goal is assigned (i.e. 66 picks) and thus provides supporting evidence for Hypothesis 8 derived from the planner model. We note however, that such support appears to be only valid for challenging goals as explained when addressing Question 6.

**Question 5** *What are the effects on work pace regulation if the goal difficulty (level) is increased?*

To describe the effects of goals on work pace regulation. We identify two types of effects. First, the effect on the initial work pace and then the effect on deceleration or acceleration as time passes. To identify the first effect, first note that the initial work pace refers to the work pace at $t = 0$. Therefore, in Table 4.3, the initial work pace is the intercept of the model affected by skill level and goal factors. In this way, Table 4.3 shows a clear main effect of goal levels in terms of increasing the initial work pace ($p < 0.001$) as is also illustrated in Figure 4.7.

Moreover, these results show that when the highest goal was assigned (i.e. 66 picks) there was an increase in the initial work pace of about 9.5% with respect to the lowest goal assigned (i.e. 47 picks). We note that this result is consistent with Hypothesis 9 derived by the planner model. However, these results are, at the same time, not supportive of Hypotheses 2 and 3 derived from the myopic model. These models predicted an increase in the starting work pace and a time shift of when the maximum work pace is achieved.

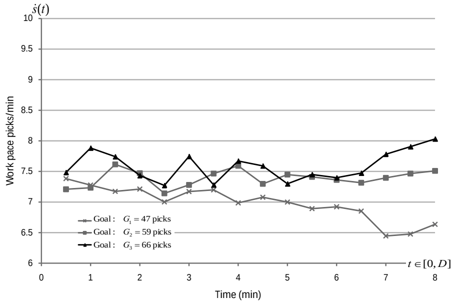
Furthermore, the fact that there is a main effect in the intercepts (starting work pace) provides evidence that planning does in fact occur, as only in the case of easy goals there is a correction (downwards) of the selected work pace and individuals actively select different initial work paces for different goals. It then appears that the act of balancing the intrinsic motivation derived from working at a certain work pace with the extrinsic motivation derived from performing at a certain level with respect to the assigned goal is done at the start of the work considering the whole working period. This is opposed to the myopic model proposed in Chapter 3, where workers constantly evaluate their motivation towards the goal and accelerate when they are proximal to the goal due to enhanced motivation.

The second effect of goals in work pace regulation is at the level of time. The results shown in Table 4.3 indicate a significant and positive interaction effect of lower goal levels (i.e. 59 and 47 picks) with time ($p < 0.01$). However, such interaction is not present when the highest goal (i.e. 66 picks) is assigned ($p > 0.1$). These results suggest that challenging goals *induce* working at a steady work pace. To our knowledge, the result that challenging goals induce a steady work pace has not been documented before and is an additional advantage of challenging goals for operational settings where steady job processing rates are desirable. These are desirable, because the estimation of the completion of job batches is more reliable and makes it easier to balance servers in a productive system.

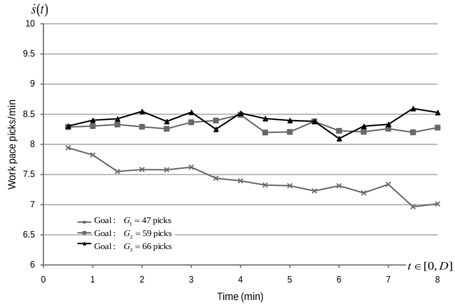
The panels in Figure 4.9, also provides indirect evidence for a most comfortable work pace, denoted as $n$, and introduced in Chapter 3 as the work pace that is naturally most preferred for a worker in the absence of any external influence. In particular, Figures 4.9a and 4.9b show that the average work pace (for individuals of Skill Level 1 and 2) is never lower than 6.25 picks/min (47 picks), suggesting the existence of a most comfortable work pace that acts as a lower threshold.

**Question 6** *What are the effects on work pace regulation if the skill level is increased under the influence of an assigned goal and deadline?*

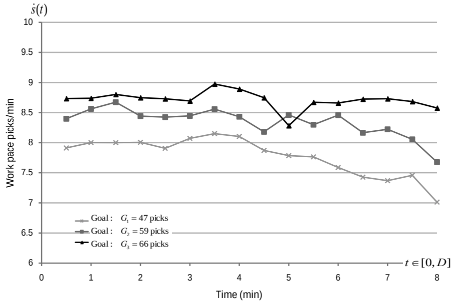
As expected, from Table 4.3, there is a positive main effect associated with increasing skill levels, where higher skill levels increase the initial work pace ($p < 0.01$), which is consistent with Hypotheses 4 and 11 of the myopic and planner models. Nonetheless, there does not appear to be an interaction effect between skill levels and time ($p > 0.1$), meaning that the skill level affects the initial work pace, but not any work pace tendencies over time.



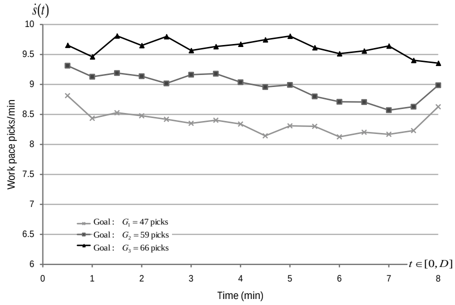

(a) Skill Level 1




(b) Skill Level 2




(c) Skill Level 3




(d) Skill Level 4

Figure 4.9: Work pace regulation across different skill levels and goals assigned

**Question 7** *What are the effects on work pace regulation when the skill level and assigned goal interact?*

Further investigation appears to reaffirm the idea that when the goal is challenging with respect to the individual's skill level, a stationary, constant work pace is induced. This idea is supported by the moderately significant interaction effect found with the time factor when an easy goal (i.e. 47 picks) is assigned to a top skilled individual (i.e. Skill Level 4), ($p = 0.0558$). Furthermore, the panels of Figure 4.9 illustrate this interaction.

Moreover, Figure 4.9b shows how the work pace regulation of the two higher assigned goals are very similar in level and in pattern, suggesting that the assigned goal of 66 picks exceeds the limits of ability of individuals with Skill Level 2. This result provides additional evidence for the existence of a skill level (i.e. denoted in Chapter 3 by $L$) that acts as an upper threshold (i.e. a concept introduced in Chapter 3). At the same time, the fact that the work pace is non-decreasing on goal difficulty, provides indirect evidence that workers are relatively insensitive to increases in the work pace (effort) up until such work pace reaches the limits of their ability. In other words, there is evidence for a relatively flat utility work pace function as depicted in Figure 3.2 of Chapter 3.

**Heterogeneity of work pace results**

One of the advantages of using HLM as a method of analysis is that it allows us to asses the variation of the estimated parameters across participants. Here, again a new advantage of goal setting for operations can be found: Challenging goals make work pace regulation significantly more predictable; the variance of the time-slope estimate for a goal of 47 picks shown in Table 4.3 is $\sigma^2_{v\{1,1,i\}} = 0.00547$, almost ten times larger than the variance of the time-slope estimate for a goal of 59 picks, $\sigma^2_{v\{1,2,i\}} = 0.00055$. A possible explanation for this is that challenging goals force individuals to work at a consistently high speed whereas a not-so challenging goal provides more freedom as to the strategy used to achieve the goal (certain individuals may opt for a steady state, others for speeding up later, but the majority may opt for a gradual decrease in the work-pace as shown in Figure 4.7).

The results also show that considerable residual variance exists at the level of a picking round and the individual picker. For this, we look at the interclass correlation coefficient (ICC) that measures the proportion of residual variance at a given level of the model with respect to the total model (Kreft and Leuw, 1998). The ICC values of 0.3343 and 0.3664 at the picking round level and at the individual level respectively, highlight the fact that most of the random effects are accounted by different picking rounds and different participants in the experiment, thus further justifying the use of HLM in the analysis of the data.

## 4.6 Quality results

Setting challenging goals may also have its limitations. Hence, we also attempted to confirm a result from goal setting (Bavelas and Lee, 1978) that states that goals may enhance performance in the dimensions measured at the expense of other dimensions that are not observed. Table 4.4 weakly confirms this by showing a marginal significant decrease in quality measured in percentage of errors when comparing errors across increasing goal levels. A repeated measures ANOVA test does not confirm differences in quality ($F(2, 160) = 1.755$, $p = 0.176$). However, a contrast between the lowest and the highest goal does yield marginal differences ($p = 0.067$).

The marginal significance may be due to the low power of the test. Even though the within-participants design of the experiment allows for a direct comparison of individual quality levels, the fact that errors are seldom observed, decreases the statistical power of the test. Nonetheless, there is weak evidence that suggests that even though a pick with errors has a negative effect

Table 4.4: Quality results across goal levels

| Assigned goal No. of picks | Performance No. of picks | Standard Error No. of picks |
|---|---|---|
| 47 | 1.844 | 0.199 |
| 59 | 1.945 | 0.241 |
| 66 | 2.333 | 0.257 |

on productivity as time lost, it appears that still, maximizing productivity alone is not perfectly aligned with minimizing quality errors.

## 4.7 Discussion

This chapter addressed two research objectives by first validating from an operations management perspective previous reports on the goal level-performance relationship and then by studying how workers regulate their work pace under the influence of a goal and a deadline. This chapter builds on the theory developed in Chapter 3 where specific hypotheses are proposed regarding the goal level-performance relationship and work pace regulation. These hypotheses were derived from two alternative decision making models; one that assumed myopic pacing decisions and another that assumed planned pacing decisions.

The results verified that as long as realistic goals are assigned, the goal level-performance relationship is increasing and then levels off when individuals reach the limits of their ability. What distinguishes these results from previous ones is that these were obtained in a context where a deadline was assigned and where participants were requested to work until the assigned deadline even if they had already achieved the goal. This then confirms the majoritarian view in goal-setting for an operational context where deadlines are set. Moreover, the results provided additional information by distinguishing how performance increases with goal levels across different skill levels. In this way, it was possible to observe how higher goals increased performance even if increasing performance was not necessary to obtain the goal.

What distinguishes this study from previous studies is that it is the first study, to our knowledge, that focuses on work pace regulation over time, under the influence of goals. In this respect, our main finding is that challenging goals induce workers to not only work at a higher work pace, but at a constant one inducing stationary job processing rates. At the same time, when workers are assigned to goals that are not challenging enough, the initial work pace tends to decrease.

Furthermore, when goals and deadlines are both present and assigned goals are not challenging, we found no evidence to support an acceleration towards the assigned goal, but instead found evidence supporting an acceleration towards the deadline. Interestingly, an analysis of variation across individuals, showed that assigning challenging goals, not only induces a steady

Table 4.5: Goal difficulty-performance hypothesis testing overview

| Questions and Answers | Evidence: Literature | Evidence: Decision model | Evidence: Empirical support |
|---|---|---|---|
| *Question 1 What are the effects on individual performance (i.e. cumulative performance of an individual measured at the end of the assigned period) if the goal difficulty (level) increases?* | | | |
| Possible answer 1 | | | |
| The goal difficulty-total performance relation for a myopic worker is unimodal, increasing and then decreasing on the assigned goal level (Hypothesis 6 and Hypothesis 9). | Erez and Zidon (1984) | Theorem 6 (Myopic model)<br>Theorem 9 (Planner model) | Unsupported |
| Possible answer 2 | | | |
| Total performance increases and then remains constant (levels off) with goal difficulty (Hypothesis 10). | Locke and Latham (1982 and 1990) | Theorem 10 (Planner model) | Supported |
| *Question 2 What are the effects on individual performance if the skill level increases under the influence of an assigned goal and deadline?* | | | |
| Possible answer 1 | | | |
| Performance (total work) increases given a skill increase (Hypothesis 7 (Myopic model) and Hypothesis 11 (Planner model)). | Erez and Zidon (1984) | Theorem 7<br>Theorem 11 | Supported |
| *Question 3 What are the interaction effects of increasing goal difficulty (level) and skill level on individual performance?* | | | |
| Possible answer 1 | | | |
| Interactions exist. Difference in performance increases between workers of different skill levels as the lower skill workers reach their maximum performance. | Erez and Zidon (1984) | | Supported |

Table 4.6: Work pace regulation investigation overview

| Questions and Answers | Evidence: Literature | Evidence: Decision model and justification | Evidence: Empirical support |
|---|---|---|---|
| *Question 4 How is the work pace regulated under the influence of a given goal and deadline?* | | | |
| Possible answer 1 | | | |
| A worker will accelerate towards the goal, reaching its maximum work-pace when he reaches the goal and then decelerate converging to the natural work pace if enough time is allowed (Hypothesis 1). | Goal gradient hypothesis (Hull, 1932; See et al., 2006 and Kivetz et al., 2006) | Theorem 1 (Myopic model) | Unsupported Acceleration towards deadline instead |
| Possible answer 2 | | | |
| A worker will set a time invariant work pace for the whole period (Hypothesis 8). | The alternative hypothesis, if there is no acceleration towards the goal. | Theorem 8 (Planner model) | Supported for challenging goals. |
| *Question 5 What are the effects on work pace regulation if the goal difficulty (level) is increased?* | | | |
| Possible answer 1 | | | |
| The work pace selected is shifted for the whole period by a constant lapse in time (Hypothesis 2).<br>When a higher goal is assigned, workers will start working at a lower work pace (Hypothesis 3). | Goal gradient hypothesis (Hull, 1932; See et al., 2006 and Kivetz et al., 2006). | Theorem 2 (Myopic model) Theorem 3 (Myopic model) | Unsupported |
| Possible answer 2 | | | |
| If the goal increases, the constant work pace increases, otherwise it decreases (Hypothesis 9). | Consistent with Parkinson Law (1962) of work pace adjustment according to goal demands. | Theorem 9 (Planner model) | Supported |
| *Question 6 What are the effects on work pace regulation if the skill level is increased?* | | | |
| Possible answer 1 | | | |
| If a worker has a higher skill level than another one, the selected work pace of the worker with a higher skill level is higher as long as the goal has not yet been achieved (when the skill level is increased (Hypothesis 4).<br>The maximum observed work pace increases when the skill level is increased (Hypothesis 5). | The literature has not investigated this question. | Theorem 4 (Myopic model) Theorem 5 (Myopic model) | Supported, but more parsimonious hypothesis supported (see bellow). |
| Possible answer 2 | | | |
| If a worker has a higher skill level than another one, the time-invariant selected work pace of the worker with a higher skill level is higher than the worker with the lower skill (Hypothesis 11). | The literature has not investigated this question. | Theorem 11 Planner model | Supported |
| *Question 7 What are the effects on work pace regulation when the skill level assigned goal interact?* | | | |
| Possible answer 1 | | | |
| Interactions exist, challenging goals induce steady work pace and eliminate any acceleration towards the deadline. | The literature has not investigated this question. | | Supported. |

work pace, but also more predictable work pace regulation patterns. In this way, we found larger deviations from the average deceleration pattern observed for non-challenging goals than from the average steady work pace pattern observed for challenging goals. Hence, operations work flow models, including queuing models and simulation models, should consider this behavior when modeling work flow under the influence of goals.

Taken together, the results show a general consistency with the planner model introduced in Chapter 3, as workers select a higher initial work pace when a higher goal is assigned and challenging goals induce a steady work pace. Both facts suggest that an initial plan is devised for the whole working period.

The results do, however, suggest that the initial plan may be subject to a control mechanism. The fact that only challenging goals induce a planning behavior may be explained by the fact that challenging goals may require workers working consistently to the best of their ability, close to their highest work pace. In agreement with Carver and Shreier (1998), when a goal is difficult to attain, the only possible strategy is to stay on course and frequently (or continuously) control that the work pace is adequate to achieve the goal on time. If a goal is then deemed, by an individual, not to be too challenging, it is possible that the individual makes the decision to not control his actual effort with respect to his planned effort and thus drifts towards his most comfortable work pace. This explanation is also consistent with the findings reported by Deci et al. (1999) stating that goals enhance attention, and thus activate mechanisms of control. This explanation, however, is a hypothesis that needs further confirmation.

Moreover, the results show evidence that suggests the existence of an internal evaluation of the work pace itself and performance with respect to a goal as described by the utility functions proposed in Chapter 3. In particular, the results support the existence of a work pace-utility rate function as described in Chapter 3 with a most comfortable work pace ($n$) and a maximum work pace ($L$) as well as the existence of a performance utility function as described in Chapter 3 with a characteristic "S" shape and goals acting as reference points.

Interestingly, the empirically obtained utility performance function valuation, suggest a desirable effect of goal setting: Goals normalize expectations on the desirability of attaining certain performance levels, even in the presence of differently skilled individuals. This normalization effect provides an explanation for the robustness of goal effects in total performance, in spite of individuals with different skill levels and personality traits. This fact can be used later to the advantage of operations managers by assigning different goals according to different production requirements over time.

The results also note the limitations of goal setting, where there is weak evidence for an increase in quality errors when participants are urged to increase their work pace. Although, a goal in productivity performance may distract the worker from, at the same time, striving towards quality. If, indeed, these two dimensions are related, as was the case in this experiment, such a trade-off may be moderated. The trade-off may be further moderated by the work station layout design as well as other mechanisms for error reduction such as enabling/disabling the relevant/non-relevant keys on a keyboard (as was done in this experiment).

## 4.8 Limitations

The study conducted here has a number of limitations. The first limitation is the time frame of a picking round which was fixed to 8 minutes. Longer times may make it more difficult for workers to sustain a steady work pace even in the presence of a challenging goal. For sufficiently long periods the incidence of fatigue may start to influence work pace regulation patterns as well. A second limitation is that feedback frequency remained constant across experimental conditions. Feedback frequency may also play a role in sustaining a steady work pace. Hence, the roles of period length and feedback frequency in work pace regulation are worth studying in future research.

Another limitation of this study is that it did not address the phenomenon in the literature known as adaptation towards the goal (Lant, 1992). Although we have found that goals robustly fix reference points for performance, it is possible that previous performance and observed performance of other co-workers may influence the performance at which reference points are fixed. Repeatedly failing to achieve a goal may affect the self-efficacy of individuals (i.e. the individual belief that a goal is attainable) and hence affect commitment towards the goal (Locke et al., 1988). Likewise, Schultz et al. (1998) have shown that in social contexts, workers adjust the work pace to match those of their peers. Hence, it would be interesting to investigate the interaction between assigned goals and peer performance in how workers evaluate their own performance.

## 4.9 Conclusions

In this chapter we tested hypotheses derived from the decision models of Chapter 3. We confirmed that performance increases with goal difficulty and then levels-off for operational contexts were a deadline is present. More importantly, we identified that challenging goals induce steady work pace regulation as opposed to non-challenging goals were the work pace decreases from an initial higher work pace.

From a managerial perspective, the results on the goal level-performance relationship validates the advice of Locke and Latham (2006) of setting challenging and realistic goals for operational contexts where deadlines exist. As long as there is commitment to achieve the goal, an increase in the goal will not reduce total individual performance. In deciding which goal to assign to a group of heterogeneously skilled individuals a manager should try to balance maximum production while minimizing frustration for failing to achieve the goal. The performance evaluation "S" curve introduced in Chapter 3 and validated in this chapter may be used to quantify the impact in terms of dissatisfaction in failing to achieve the goal.

The work pace regulation study has specific implications for operations management. Specifically, challenging goals induce a steady work pace with lower variation in work pace regulation patterns. This is a previously unreported advantage for challenging goals in operations management contexts where stationary job processing rates and predictability are desirable. More stationary and predictable job processing rates make planning easier in operational management contexts and make service times more reliable. Furthermore, reducing variability in work pace and steady job processing rates, increase effective capacity when several work stations are interconnected.

In addition, the results in work pace regulation have implications for operations management practices. In particular, consider the question of a manager that wants to verify if a goal is demanding workers to work at the best of their ability. Based on our results of work pace regulation, a manager may verify whether the worker is working at steady state and from that infer if the worker is working to the best of his ability. Moreover, if the goal is increased and the same steady work pace is observed it can be confirmed that the worker is indeed working to the best of his ability. In the case a manager wants to verify in real time whether a worker would be able to meet the deadline on time the insights from this study show that he should extrapolate the current work pace and not expect an acceleration towards the goal.

Finally, the study presented in this chapter provides additional information for work flow models as identifiable work pace regulation patterns exist for different skill level assigned goal combinations. Moreover, the heterogeneity of work pace regulation patterns can also be modeled and predicted where there is lower heterogeneity when challenging goals are assigned. Queuing and simulation models may also be enriched by the insights of this study, especially when specific goals and deadlines are set. Already, queuing and simulation models assume stationary job processing rates, these models may be model the effects of goals by incorporating non-stationary if the goal is not perceived as challenging and stationary behavior otherwise.

# Chapter 5

# Managing Warehouse Efficiency and Worker Discomfort Through Enhanced Storage Assignment Decisions

## 5.1 Introduction

In the context of supply chain optimization, the optimization of material handling operations within a warehouse has received considerable attention in the literature with a particular focus on order picking operations (for a review, see De Koster et al., (2007))). Such a focus is hardly surprising as it has been reported that in a typical warehouse 55% of the operational costs (Frazelle, 1996) and 12% of the total supplier-retailer logistics costs (Van der Vlist, 2007) are due to order picking activities. To maximize the efficiency of order picking operations, five approaches have been proposed. The first approach consists of assigning items to different storage locations based on their popularity (Heskett, 1963). The second approach considers the batching of orderlines in a single picking route (Gademann and Van de Velde, 2005), while the third approach concerns devising order picking routes within the storage area (Roodbergen and de Koster, 2001). The fourth approach consists of organizing picking activities into zones (Yu and De Koster 2008). Lastly, the fifth approach is the redesign of layout structure in terms of the number of pick aisles, number of blocks and length of the pick aisle (Roodbergen et al., 2008). All five approaches maximize efficiency by minimizing travel distance.

The reason why most order picking optimization models focus on minimizing walking distances is that travel is estimated to be responsible for about 55% of the total picking time per order (Frazelle, 1996). Warehouse designs such as sequential zone picking and forward-reserve storage are examples of design efforts to reduce walking distances. In a sequential zone picking system, the walking distances are reduced by transferring partial orders between zones using mechanical devices such as conveyors. In the case of forward-reserve configurations, walking distances are reduced by concentrating most of the picking activities in a small “forward” area that is replenished from a larger “reserve” storage area (Bartholdi and Hackman, 2008).

As walking distances decrease by various means, the relative importance of other activities increases. Specifically, in the literature, most of the storage location assignment models disregard the time spent on retrieving and searching for items, although Tompkins et al.’s (2003) report that these activities account for 35% of total picking time. Most papers explicitly or implicitly assume that a pick always requires the same amount of time, regardless of the level (height) at which it is picked, the quantity picked and the size and weight of the item to be picked.

Only a few papers have recognized the importance of retrieving and searching actions, by acknowledging the influence of a third dimension (height) on order picking times present in shelf picking contexts (Saccomano, 1996; Jones and Battieste, 2004; Petersen et al., 2005). These articles define a strategy where items that are picked more often should be located in picking locations that lie within the so-called “Golden Zone”, the area between the waist and the shoulders of “average” pickers (Jones and Battieste, 2004).

The economic justification for this allocation strategy is that items within the “Golden Zone” are expected to take less time to identify and retrieve than items outside this zone. Nonetheless, the precise effect of height on searching and retrieving times is unknown, let alone any interaction effects between heights and product characteristics (e.g., weight of the product or volume). Moreover, the extent to which the “golden zone” allocation strategy actually minimizes cycle time remains to be determined. After all, time savings due to picking at “Golden Zone” positions must be weighted against time savings from picking at positions closer (in the 2D sense) to the starting point of the route.

The “Golden Zone” allocation strategy also has a social justification when considering the well-being of order pickers. Working in the “Golden Zone” may prevent working in extreme postures (Jones and Battieste, 2004). These extreme postures occur when picking at locations outside the “Golden Zone” and may be uncomfortable for the picker even if he deals with light products (Kruizinga et al., 1998). Discomfort felt by employees is a pervasive problem in warehouses and has been found to be a predictor for future long-term muscular pain (Hamberg-van Reenen et al., 2008) as well as occupational disorders such as the so-called Low Back Disorders (LBDs). The importance of LBD’s is highlighted by reports of an American insurer that LBD-related claims account for 16% of the total worker claims and 33% of total worker claim costs (Snook, 1982 and Webster and Snook, 1994).

Reducing discomfort is then directly related to the well-being of workers and may also yield long-term economic benefits through higher productivity (Kuijt-Evers et al., 2007), reduced worker health-related costs, absenteeism and drop-out rates, which are particularly important in countries with a deficit of blue-collar employees. Nonetheless, it is worth noting that discomfort itself has been recognized by the European Union Machinery Directive as a condition that should be minimized along with other factors that affect worker well-being, including fatigue and psychological stress, by taking ergonomic principles into account (ECD 2006).

The efforts to reduce discomfort are in-line with Corporate Social Responsibility practices. Corporate Social Responsibility (CSR) is an umbrella term used to address the concern with the well-being of the stakeholders of the firm, including its employees as one of the main stakeholders (Maignan and Ralston, 2008). In a context where CSR is perceived as relevant for the sustainability of the firm, any efforts for increasing the well-being of employees in the workplace at reasonable financial costs are well received. Already, Maignan & Raltson (2002) report that 53% of American firms explicitly mention CSR on their website.

Hence, we define the social goal of product location assignment for order picking activities as that of minimizing discomfort. The well being of an employee depends on other factors as well, but we focus on the human factor that is directly affected by storage allocation decisions.

In this chapter we seek to make better tactical storage location decisions with respect to two criteria: 1) a short-term economic criterion (i.e. minimizing total order picking time, but excluding long-term health savings that are more difficult to quantify) and 2) a social criterion (i.e. minimizing average discomfort). We propose a methodology to combine both economic and social goals in tactical storage location decisions; by proposing a methodology that considers both types of goals we provide an interface between insights of operations management and insights from human sciences. In a sense, this chapter can be considered a response to the challenge posited by Boudreau et al. (2003) and Gino and Pisano (2008) to include human aspects in conventional operations decisions. Further, our research as presented in this chapter goes beyond conceptual papers on the application of CSR in operations, such as the one by McAdam (2003), by providing empirical evidence for possible improvements of the well-being of employees via enhanced operational decisions.

It must be noted that the proposed combination of goals may be non-trivial as has been often claimed in practice and in the scientific literature. Peacock (2002) suggests that a tension between human centered criteria and operational performance criteria exists, in particular if the operational performance is only short-termed. On the other hand, Dul et al. (2004) show that social goals expressed in ergonomic standards may yield economic benefits, which suggests a certain degree of alignment between social and economic goals. This chapter aims to illustrate the debate between the existence of conflict or alignment in social and economic goals by considering the specific context of storage location decisions for order picking activities and quantifying the extent to which there is a trade-off between both goals.

Although we acknowledge that practitioners and industrial engineers often combine both economic and social criteria in their design criteria, this is typically done in an ad-hoc manner. Our results will inform practitioners and industrial engineers by quantifying the "economic" and "ergonomic" costs involved in pursuing an ergonomic or an economic-friendly solution. Further, based on the trade-off results, we will give recommendations on how to obtain near-efficient solutions that balance both economic and social goals with the use of simple decision rules (i.e. heuristics).

We restrict our study to a particular setting of order picking, where retrieval activities are likely to contribute significantly to the total cycle time, and thus influence the efficiency of order picking systems and increase the exposure of workers to discomfort. The particular setting that we consider is picker-to-part order picking systems (for an overview of order picking systems see Tompkins et al., 2003) where workers walk and retrieve items from shelves. These systems are usually organized into zones, where orders are partially picked in one zone and then transferred, via conveyors, to be completed in other zones; these are typically referred to as "pick and pass" configurations. These systems are used by the majority of warehouses in the Western world (De Koster et al., 2007) and are characterized by typically many picks per time unit with a relatively limited amount of walking. Furthermore, each picker only picks one or a few items per order from multi-leveled shelves, since the remainder of the order is picked by other people in other zones. It is also worth noting that there is only one picker assigned per zone, thus avoiding congestion issues (Gue et al., 2006).

Our approach differs from storage location models in the literature (such as that of Petersen et al. (2005)), in that we formulate expressions using empirical data collected at two warehouses, thus providing empirical evidence for considering differences in picking heights. We then use these empirical expressions in a bi-objective assignment model that takes both the cycle time and the picker's discomfort into account.

This chapter is organized as follows. In Section 5.2 we conduct an empirical study to investigate the effects of different heights on retrieving times and on discomfort levels. Next, in Section 5.3, we propose a multi-objective model (with an economic and a social goal) to identify non-dominated solutions and possible trade-offs between economic and social goals. Finally, in Section 5.4, we give conclusions and insights for further research.

## 5.2 Empirical study of order picking activities

We conducted our empirical studies in two distinct warehouses that share two common characteristics in line with the scope of this chapter. When selecting the warehouses for our empirical study we required that these had certain similarities and dissimilarities. On one hand, the warehouses must be similar in that the order picking activities must be organized in zones sequentially so that the walking distances are limited, and the retrieving times must be an important component of the total picking cycle times. Furthermore, to enable analysis of the influence of the picking height, the items of both warehouses should be stored in totes at multiple levels. In addition, we require that both warehouses have a significant proportion of picking tours that only visit one location, which makes the results easier to compare between warehouses. On the other hand, we also allowed for differences in order profiles, particularly in product characteristics (see Section 5.3.4) and differences in layouts for selecting the warehouses to obtain insights in the potential generalizability of the empirical findings.

The first warehouse is the main distribution center of Yamaha Motor for motorized vehicles' spare parts in Europe. The warehouse has a large assortment of over 150,000 Stock Keeping Units (SKUs). The order picking activities are organized in areas and zones. We conducted a study in the main area for fast moving items of small and medium size that is sub-divided into 32 zones. Within this area, in each pick route, exactly one location is visited. Each zone has a computer terminal next to the depot, where the picker scans the item picked, confirms the pick, and views the next orderline to pick. In addition, a pick-to-light system with a red blinking display is used to indicate the location from which an item must be retrieved.

The second warehouse is that of Sorbo Distribution Center (DC), a main importer and distributor in The Netherlands of non-food products for supermarkets. Given that the Sorbo DC deals with fast-moving items with a relatively low unitary value, the primary concern for Sorbo DC is cost efficiency in order picking operations. Similar to the Yamaha Distribution Center (DC), Sorbo's warehouse is organized in 24 zones where one picker is responsible for picking items per zone. Sorbo also works with a pick-to-light system, however, picked products need not be scanned at the depot. Confirmation of the picks is achieved by indicating the number of units picked at the picking locations themselves. Another important feature is that the stored products are re-arranged before the start of every shift using a dynamic picking system concept where the picking positions constitute a forward area and storage positions behind the picking positions constitute a reserve area. This system allows for the handling of a large assortment in a small area at high picking rates (De Koster et al. 2007, Yu and De Koster, 2008). Most of the routes, about 85%, visit only a single location.

In both warehouses there are three equally spaced picking levels at heights ranging from 0.25 m to 1.90 m in the case of Yamaha DC and 0.20 m to 1.40 m in the case of Sorbo DC. See Figure 5.1 for a simplified layout of a typical zone for the Yamaha DC and Sorbo DC. While the Yamaha DC has 145 product locations available per zone, the Sorbo DC has 120 locations available per zone and a simpler layout. The Yamaha DC has typically heavier and less voluminous items than the Sorbo DC as the items of the Yamaha DC are mostly made of metal while the Sorbo DC items are usually made of plastic.

### 5.2.1 Empirical study of picking cycle time

We define the picking cycle time as the time lapse from the receipt of an orderline at the picker's terminal until dropping the products in a bin at the depot. The picking cycle can be broken down into the following activities: receipt of a new orderline, walking to the picking location, searching the specific location and retrieving the units of a product from such a location, walking back with the units to the depot, dropping off the picked products at the depot, and finally

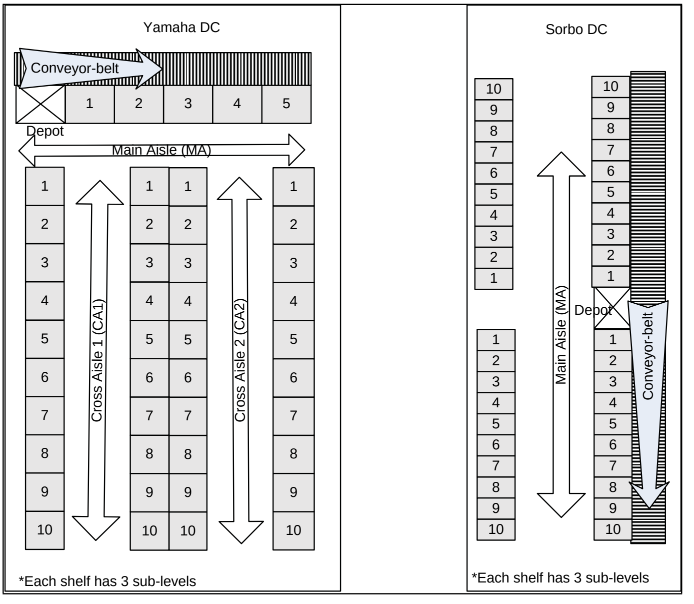



Figure 5.1: Simplified layout of a typical Yamaha DC and Sorbo DC picking zone.

confirming the pick at the depot. A number of drivers can influence each of the order picking activities. We classify these drivers as either location factors, or product factors. Our choice for selecting explanatory variables for cycle time is driven by our goal of enhancing tactical storage location decisions. Hence, we include location factors as well as interaction effects of location with product factors, but we do not include other factors (such as salaries or motivational incentives) that are out of the scope of storage location decisions, even though such factors may still influence cycle time indirectly. Further, for the cases studied there was not any variation in these factors in order to estimate their influence. Salaries and incentive schemes are the same for all the personnel within the order picking area of a warehouse. Individual differences are also irrelevant for the analysis due to the tactical nature of storage decisions: storage decisions can not be changed too frequently to adapt specifically for a given individual. Thus, storage decisions need to be designed for a given population.

Table 5.1: Picking time breakdown analysis.

| Picking sub-activities | Main effects | | | | | | | | Interaction effects | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Location factors | | | | | Product factors | | | | | |
| | $MA$ | $CA$ | $CN$ | $L^{(k)}$ | $LB$ | $M$ | $V$ | $Q$ | $M * L^{(k)}$ | $V * L^{(k)}$ | $Q * L^{(k)}$ |
| New orderline receipt | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a |
| Walk from depot | + | + | + | ? | ? | n/a | n/a | n/a | n/a | n/a | n/a |
| Retrieve & search item | n/a | n/a | n/a | +/- | + | + | + | + | ? | ? | ? |
| Return to depot | + | + | + | n/a | ? | ? | ? | ? | n/a | n/a | n/a |
| Drop picked item(s) | n/a | n/a | n/a | n/a | n/a | ? | ? | ? | n/a | n/a | n/a |
| Confirm orderline | n/a | n/a | n/a | n/a | n/a | ? | ? | + | n/a | n/a | n/a |

Location factors

| | | |
|---|---|---|
| $MA$ | : | Section number in the main aisle. |
| $CA$ | : | Section number in the cross aisle (valid only for Yamaha DC). |
| $CN$ | : | Cross aisle number (valid only for Yamaha DC). |
| $K$ | : | Picking levels set $K = \{1, 2, 3\}$ where 1 is the lowest level and 3 the highest. |
| $L^{(k)}$ | : | 1 if picked at level $k \in K$; 0 otherwise. |
| $LB$ | : | 1 if picked from a large bin; 0 otherwise (valid only for Yamaha DC). |

Product factors

| | | |
|---|---|---|
| $Q$ | : | Quantity picked. |
| $M$ | : | Unit mass of the product. |
| $V$ | : | Unit volume of the product. |

It is logical to assume that while 2D location factors (i.e. $MA$, $CA$ and $CN$) positively influence walking times, the different picking levels only influence retrieving and searching times. In the case of the Yamaha DC, we also include picking from locations with large bins ($LB$). This may influence the retrieving times because large bins require the arms to be stretched slightly further to reach the products.

Intuitively, the product factors mainly influence retrieving times and possibly walking times due to greater difficulty in carrying items. It may be possible, though, that product factors also influence the time it takes to drop off products, the time to return to the depot or even the time to confirm an order. In particular, the quantity picked may influence the time to confirm an order as items are counted in this activity.

Finally, in the case of retrieving times there are possible interaction effects between the pick level and the product factors. For example, it may well be that it is additionally difficult to manipulate heavy and/or voluminous items at a top storage level than at an intermediate, "Golden Zone" level, however this is to be verified empirically. We summarize our hypotheses in Table 5.1 marking almost certain effects with an "+" or a "+/-" (all of which are positive effects, except for the case of height which we hypothesize has a curvilinear effect "+/-"), potential effects with a "?" and no effects with a "n/a" (i.e. not applicable).

Using the table, we can formulate the picking cycle time $CT^Y$ at the Yamaha DC in terms of the hypothesized effects. We detail how our model is built as follows. As the 2D location factors directly influence the walking distances, it is logical to assume that these factors ($MA$,

$CA$ and $CN$) linearly influence cycle times considering a constant walking speed, where $b_1$, $b_2$ and $b_3$ are the corresponding linear coefficients to be estimated. The different levels $L^{(k)}$ are modeled as dummy variables with the medium level $k^* = 2$ as the reference level to avoid perfect multicollinearity with $\alpha^{(k)}$ corresponding to the additional time required to retrieve an item at $k$. For simplicity, the quantity to be picked is also assumed to influence the retrieving times and dropping-off activities linearly. This is actually an approximation of a more complex relationship as certain items may be grabbed in batches. Note that the incremental pick quantity (incremental over 1) is used in the model and not the quantity picked itself. This is done because most often one piece of each product is needed. We can interpret coefficient $b_4$ as the additional time required to pick one additional item. The main effects are completed by not making a priori assumptions on the effects of volume and mass, using general functions $f(M)$ and $g(V)$ as these are unknown and several functional forms must be tested. Further, to account for possible interaction effects of quantity, mass and volume effects with heights $k \in K$, we introduce $\beta^{(k)}$, $\gamma^{(k)}$ and $\lambda^{(k)}$ linear coefficients respectively. The formulation of cycle time for the Yamaha DC where $k^* = 2$ is thus:

$$\begin{aligned} CT^Y &= b_0 + b_1 MA + b_2 CA + b_3 CN + \sum_{k \in K, k \neq k^*} \alpha^{(k)} L^{(k)} \\ &= + b_4(Q-1) + b_5 f(M) + b_6 g(V) + b_7 LB + IN + \varepsilon, \end{aligned} \tag{5.1}$$

where $IN$ contains the interaction effects given by the following relationship:

$$IN = (Q-1) \sum_{k \in K, k \neq k^*} \beta^{(k)} L^{(k)} + f(M) \sum_{k \in K, k \neq k^*} \gamma^{(k)} L^{(k)} + g(V) \sum_{k \in K, k \neq k^*} \lambda^{(k)} L^{(k)} \tag{5.2}$$

For the Sorbo DC, the factors $CA$, $CN$ and $LB$ do not apply and therefore the predicted relationship for its cycle time $CT^S$ simplifies to:

$$CT^S = b_0 + b_1 MA + \sum_{k \in K, k \neq k^*} \alpha^{(k)} L^{(k)} + b_4(Q-1) + b_5 f(M) + b_6 g(V) + IN + \varepsilon. \tag{5.3}$$

### Data collection

To analyze the effects of location and product characteristics on cycle times, we obtained real operational data at both warehouses from their warehouse management systems. The warehouse management systems provided detailed information about the location of each pick (i.e. level, aisle number, section number) and characteristics of the product to be picked (i.e. mass, volume, length, width and height). The use of the warehouse management systems' data provides several advantages over traditional time studies (Barnes, 1968) for estimating cycle times given different location and product related products. The main advantage is the possibility to obtain a large set of observations with little effort as the day to day operational data is automatically stored in the system and the impact of several cycle time drivers can be quantified simultaneously. For traditional time studies, separate measurements would be required for every combination of factors: height, 2D location, product weight and volume, rendering it a very time-consuming and impractical method for most applications in which a large number of combinations exist. Further, unlike typical assembly tasks with pre-defined and standardized micro-movements, order picking operations involve a large array of distinct micro-movements depending on the product and location characteristics.

Another advantage of using data directly from warehouse management systems is that observations are taken under normal operating conditions without any interference of a video camera or a researcher, hence possible distortions on the data set are minimized. Finally, as information about the regressors are obtained electronically, the possibility of measurement errors is very low compared to time studies.

However, using data directly from a warehouse management system also has certain limitations. One of the limitations of field data is the inability to control variables. However, the significant variability in the picks (different product sizes, masses, pick locations) over several days of operation mitigates this potential limitation. In the case of the Yamaha DC, we obtained 19,380 observations from a period of three picking days with two shifts per day and 20 order pickers working simultaneously. In the case of the Sorbo DC, we obtained 24,260 observations in a period of two days with 24 pickers working simultaneously in a single shift.

Another limitation is the fact that cycle times are not measured directly in the warehouses; only the instants at which the orderlines are confirmed and registered. Thus, only the time lapse between two consecutive picks is known, but not the *actual* time required for each pick. It is important to note that the practice of only registering confirmation times is a common practice in warehouse management systems. In that sense, the warehouses in our study are quite representative of what can be found in other warehouses. In the next section we show how to minimize the effect of this limitation.

### Dealing with multiple outliers

As mentioned, the main challenge in analyzing the data sets of both warehouses is that there is a difference between the data we can get and the data we need. The warehouse management systems at the Yamaha DC and Sorbo DC provide the times at which picks are confirmed (that is, finished), but not the times at which a pick was started by an employee. When subtracting consecutive confirmation times, we obtain in most cases the desired cycle time. However, sometimes the difference between two confirmation times may also include an unobservable waiting time that is the time between the completion of one pick and the start of the next. A preliminary time study with 150 observations in each warehouse showed that about 25% (20%) of the picks at the Yamaha DC (Sorbo DC) have waiting times.

The picks with waiting times are of two types. The first type relates to picks interrupted by disruption events such as system breakdowns and breaks (including workers going to the restrooms or that take time to talk with their colleagues or supervisor) and makes up 10% (8%) of the total picks at the Yamaha DC (Sorbo DC). The second type relates to idle time due to the excess capacity of the picking system and involves 15% (12%) of the total picks at the Yamaha DC (Sorbo DC).

As a result, the data sets have multiple outliers that are dealt with in two stages. In a first stage, cut-off times are set to eliminate "obvious" outliers from the preliminary study. These cut-off times are based on the maximum observed cycle times in the preliminary study that did not have any waiting times. For the Yamaha DC it was determined that main aisle picks do not exceed 52 seconds and that cross aisle picks do not exceed 55 seconds. In the case of the Sorbo DC, the cutoff time was established at 26 seconds. With this procedure 13% (9%) of the observations obtained at Yamaha DC (Sorbo DC) where deleted from the sample. This meant that most of the picks with waiting times caused by disruptions where deleted from the sample given that 80% of these exceeded twice the cut-off time established. Once the more "obvious" outliers were removed from the sample, the number of observations remaining for the Yamaha DC and Sorbo DC are $13,216$ and $19,898$, respectively.

For the second stage, a statistical treatment to deal with outliers is performed on both samples. Classical identification techniques for outliers that use common distance measures such as Mahalanobis or Cook's fail in our study because the computed distance measures are based on the covariance matrix of the observations which may be already biased towards the outliers (Wisnowsky, 1999). As a result, these techniques suffer from a phenomenon called "masking" where outliers are falsely classified as inliers. In addition, these techniques may also suffer from "swamping" errors where inliers are classified falsely as outliers.

To reduce the influence of multiple outliers, several techniques to classify outliers have been proposed. Wisnowsky (1999) gives a comprehensive review. However, each technique has its advantages and drawbacks and no specific multiple-outlier analysis technique has been deemed superior under all circumstances. For our analysis, we first explore the data using quantile regression which has been suggested in the literature for cases where relevant unobserved variables exist (Koenker and Bassett, 1978) as in the case of unobserved waiting times. The technique involves calculating an unbiased estimator of the quantile $\tau$ of dependent variable $\mathbf{y}$ conditioning on $n$ regressors: $Q_Y(\tau \mid \mathbf{X})$, where $\mathbf{X}$ is the $|T| \times n$ observed variables matrix. As a result, the array of coefficients $\mathbf{b}$ is the solution to the following minimization problem where $T$ is the set of observations:

$$\min_{b \in \mathbb{R}^n} [ \sum_{t \in \{T : y_t \geq \mathbf{x_t}'\mathbf{b}\}} \tau \left| y_t - \mathbf{x_t}'\mathbf{b} \right| + \sum_{t \in \{T : y_t < \mathbf{x_t}'\mathbf{b}\}} (1-\tau) \left| y_t - \mathbf{x_t}'\mathbf{b} \right| ]. \tag{5.4}$$

When using quantile regression we can, for example, perform a regression on the median by using a value of $\tau = 0.5$. Such a regression has the advantage that it is typically less sensitive to extreme values than the average used in Ordinary Least Squares (OLS) because data is ranked instead of averaged out. Moreover, quantile regression provides additional information as it allows us to explore the behavior of the sample by showing how different segments (quantiles) of the observed data are influenced by the regressors. The technique has been used successfully in ecology where differences in the population are acknowledged. In the case of the data sets available, we expect that a quantile $\tau < 0.5$ will have the best model fit. This is due to the fact that most of the outliers lie in the upper quantiles since additional waiting times will only increase the values of the observations.

Once we are able to explore the data using different quantiles and compare the resulting model fits we are then able to explore which empirical relationships are more representative of the data. As the relationships obtained are only explorative in nature, we then apply an M-robust regression to confirm the exploratory findings. M-robust regression (Huber, 1964) is a technique recommended for dealing with multiple outliers and addresses the problem by assigning less weight to probable outliers in an iterative procedure. The algorithm starts by running a simple OLS regression and then reduces the weight of the observations with greater residuals. Thus, the weighted standard errors are minimized as shown in equation (5.5). The procedure is repeated until the change in the regression coefficients is negligible.

$$\min_{\mathbf{b}\in\mathbb{R}^n} \sum_{t\in T} w_t(y_t - \mathbf{x_t}'\mathbf{b}). \tag{5.5}$$

There are several functions available to determine the weights $w_t$. In particular we use the method of (Huber, 1964). In this case, the weights are given by the following relationship where $c$ is a constant set to $c = 1.345\sigma$ and $e_t$ is the residual of the $t$-th observation obtained from the previously applied weighted regression.

$$w_t = \begin{cases} 1 & \text{if } |e_t| \leq c, \\ c/|e_t| & \text{if } |e_t| > c. \end{cases} \tag{5.6}$$

## Statistical analysis

Using relationships (5.1) and (5.3) corresponding to the Yamaha DC and Sorbo DC, we tested for main location effects, main product effects, as well as interaction effects. We used piecewise linear regression to explore possible non-linearities of mass and volume, i.e. for $f(M)$ and $g(V)$. However, interaction effects with different segments of the piecewise relations appeared not to add significantly to the quality of the fit, while increasing the complexity of the model to a large extent. The most parsimonious solution for both data sets was to include only volume as a potential factor, thus excluding mass. Apparently, volume is a better proxy than mass to handle complexities such as easiness to grab a product or easiness to retrieve a product from its location. This is confirmed by the fact that we did not find significant results when mass categories were included, not even at a 0.1 significance level. As a result, the final relationship tested for both data sets is given as follows:

$$\begin{aligned} CT^Y = b_0 + b_1 MA + b_2 CA + b_3 CN + \sum_{k \in K, k \neq k^*} \alpha^{(k)} L^{(k)} \\ + b_4(Q-1) + b_5 LV + b_6 HV + IN + \varepsilon, \end{aligned} \tag{5.7}$$

where:

| | | |
|---|---|---|
| $LV$ | : | Low volume item (1 if $V \leq 0.05$ dm$^3$; 0 otherwise) |
| $HV$ | : | High volume item (1 if $V > 5$ dm$^3$; 0 otherwise) |

$$IN = (Q-1) \sum_{k \in K, k \neq k^*} \beta^{(k)} L^{(k)} + LV \sum_{k \in K, k \neq k^*} \gamma^{(k)} L^{(K)} + HV \sum_{k \in K, k \neq k^*} \lambda^{(k)} L^{(k)} \tag{5.8}$$

Note that for the Sorbo DC, the relationship is similar to the one shown in (5.7) with the difference that two 2D location factors are excluded ($CA$ and $CN$).

Table 5.2 and Table 5.3 show the results of the empirical cycle time model for the Yamaha and Sorbo DC respectively. Results have been obtained using the open-source statistical analysis software “R” with the “Quantreg” (Koenker, 2008) add-on package for quantile regression analysis. For comparison purposes, the empirical model is built using three distinct procedures: that of ordinary least squares regression, quantile regression (Q) for different $\tau$ quantiles and the built-in MASS package for M-robust regression (M-R.R.) analysis.

The results of both data sets show that the different methods agree in the direction of the main effects, and to a certain extent in the magnitude. This implies that the results are moderately robust, which in turn suggests that the impact of the outliers is limited. In addition, it is also interesting to compare across the quantile regression models using the $R^1$ parameters. This parameter is a measure of fit analogous but not comparable to $R^2$. See (Koenker and Basset, 1999) for details. It appears that lower quantiles provide better fits although this effect reduces as the quantiles get lower. The variation in the $R^1$ seems to confirm that the model suffers from some “inflated” observations located mainly at the upper quantiles ($\tau > 0.9$).

The application of the M-robust regression method does appear to increase the overall fit of the model by yielding a 30.6% $R^2$ for the Yamaha DC and 40.4% $R^2$ for the Sorbo DC (using the OLS procedure 20.2% and 22.4% of model fit was obtained for each warehouse, respectively). The coefficients estimated with the M-robust procedure are used as input in the next section for a trade-off analysis between economic and cycle time objectives.

We note that because the data came from normal operational conditions it was influenced by several unobserved effects, such as employees taking micro-pauses to talk to colleagues, em-

Table 5.2: Yamaha DC, empirical cycle time model.

| Variables | OLS | Q $\tau = 0.2$ | Q $\tau = 0.4$ | Q $\tau = 0.5$ | Q $\tau = 0.6$ | Q $\tau = 0.8$ | M-R.R. |
|---|---|---|---|---|---|---|---|
| (Intercept) | 18.105*** | 11.873*** | 15.123*** | 16.706*** | 18.564 | 24.095*** | 17.378*** |
| $MA$ | 0.762*** | 0.820*** | 0.652*** | 0.558*** | 0.528*** | 0.419*** | 0.621*** |
| $CA$ | 1.257*** | 1.583*** | 1.541 | 1.478*** | 1.393*** | 1.013*** | 1.381*** |
| $CN$ | 1.401*** | 1.823*** | 1.778*** | 1.665*** | 1.520*** | 1.000*** | 1.551*** |
| $L^{(1)}$ | 1.084*** | 1.117*** | 1.286*** | 1.091*** | 1.285*** | 1.199*** | 1.203*** |
| $L^{(3)}$ | 0.272 | 0.207 | 0.392* | 0.403 | 0.354 | 0.323 | 0.303* |
| $Q-1$ | 0.748*** | 0.573*** | 0.955*** | 1.080*** | 1.238*** | 1.359*** | 0.963*** |
| $LV$ | -0.391* | -0.259 | -0.568*** | -0.542** | -0.696** | -0.753* | -0.537*** |
| $HV$ | 0.182 | 0.380 | 0.880* | 0.627 | 0.761 | 0.444 | 0.522 |
| $LB$ | 0.860*** | 1.007*** | 0.839*** | 0.947*** | 0.885*** | 1.008*** | 0.894*** |
| $(Q-1)*L^{(1)}$ | 0.623** | 0.761** | 0.412** | 0.339 | 0.215 | 0.566*** | 0.524*** |
| $(Q-1)*L^{(3)}$ | 0.045 | 0.094 | 0.106 | 0.128 | -0.003 | 0.134 | 0.036 |
| $LV*L^{(1)}$ | 0.169 | 0.083 | 0.481 | 0.602 | 0.471 | -0.004 | 0.265 |
| $LV*L^{(3)}$ | 1.368*** | 0.839** | 1.018*** | 1.090*** | 1.384*** | 1.773*** | 1.335*** |
| $HV*L^{(1)}$ | 1.299 | 0.593 | 0.169 | 0.684 | 0.798 | 1.308* | 0.824 |
| $HV*L^{(3)}$ | -0.016 | -0.044 | -0.753 | -0.023 | -0.061 | -0.047 | -0.105 |
| $R^1$ | -.- | 0.182 | 0.188 | 0.179 | 0.162 | 0.097 | -.- |
| $R^2$ | 0.202 | -.- | -.- | -.- | -.- | -.- | 0.306 |

OLS: Ordinary Least Squares,Q $\tau$ quantile regression at quantile $\tau$
M-R.R.: M-Robust regression method.
Significance levels: $p \leq 0.05(^*)$, $p \leq 0.01(^{**})$, $p \leq 0.001(^{***})$. Time given in seconds.
$n^{CTY}$ =13,316

Table 5.3: Sorbo DC, empirical cycle time model.

| Variables | OLS | Q $\tau = 0.2$ | Q $\tau = 0.4$ | Q $\tau = 0.5$ | Q $\tau = 0.6$ | Q $\tau = 0.8$ | M-R.R. |
|---|---|---|---|---|---|---|---|
| (Intercept) | 8.310*** | 5.333*** | 6.333*** | 7.000*** | 7.818*** | 10.400*** | 7.556*** |
| $MA$ | 0.590*** | 0.667*** | 0.667*** | 0.667*** | 0.636*** | 0.600*** | 0.629*** |
| $L^{(1)}$ | -0.131 | 0.000 | 0.000 | 0.094 | 0.000 | 0.000 | 0.055 |
| $L^{(3)}$ | 0.068 | 0.333*** | 0.333*** | 0.333*** | 0.182* | -0.200 | 0.172* |
| $Q-1$ | 1.083*** | 1.000*** | 1.250*** | 1.250*** | 1.364*** | 1.429*** | 1.222*** |
| $LV$ | -0.094 | -0.333*** | -0.333*** | -0.500*** | -0.545** | 0.000 | -0.368** |
| $HV$ | 1.031*** | 0.237 | 0.667*** | 1.000*** | 1.182*** | 2.000*** | 0.880*** |
| $(Q-1)*L^{(1)}$ | 0.007 | -0.111 | -0.117 | -0.028 | -0.091 | -0.079 | -0.103* |
| $(Q-1)*L^{(3)}$ | 0.121 | 0.000 | -0.028 | -0.012 | -0.023 | 0.171 | 0.033 |
| $LV*L^{(1)}$ | -0.501* | 0.000 | 0.000 | -0.167 | -0.090 | -1.000* | -0.217 |
| $LV*L^{(3)}$ | 0.347 | 0.000 | 0.000 | 0.167 | 0.273 | 0.800 | 0.315 |
| $HV*L^{(1)}$ | 0.820*** | 0.667 | 0.333* | 0.333 | 0.818* | 1.600*** | 0.581*** |
| $HV*L^{(3)}$ | 1.305*** | 0.667 | 0.667** | 0.333 | 0.909 | 3.000*** | 0.993*** |
| $R^1$ | -.- | 0.214 | 0.198 | 0.181 | 0.157 | 0.102 | -.- |
| $R^2$ | 0.224 | -.- | -.- | -.- | -.- | -.- | 0.404 |

OLS: Ordinary Least Squares,Q $\tau$ quantile regression at quantile $\tau$
M-R.R.: M-Robust regression method.
Significance levels: $p \leq 0.05(^*)$, $p \leq 0.01(^{**})$, $p \leq 0.001(^{***})$. Time given in seconds.
$n^{CTS}$ =19,898

ployees correcting small mistakes in the confirmation of picks, or very brief delays in information processing at the terminals. We verified if fatigue may influence the results by incorporating dummy variables representing the shift intervals. However, no significant effects were found. To account for hetereoskedasticity, the errors shown in the table are White, hetereoskedasticity-consistent errors.

Besides comparing the different techniques, a more noteworthy comparison is that across the data sets of the two companies. The main location and product factors have significant effects on cycle times that point in the same direction for both warehouses. Furthermore, standardizing the coefficients of the results shown in Table 5.2 and Table 5.3, there is a clear ranking of the strength and relevance of the factors. We mention them in descending order: (1) 2D location factors (i.e. $MA$, $CA$, $CN$), (2) quantity to be picked, (3) height level of location. The main effects found for pick height confirm our hypothesis that different heights do require different retrieving and searching times. However, the effects are more evident in the Yamaha DC than the Sorbo DC because the Yamaha DC has a larger range of heights than the Sorbo DC.

In fourth place in the rankings are the interaction effects found in the picking levels. As for the interaction effects, these generally point in the same direction for all methods tried. However, in the Yamaha DC small items located at upper levels take more picking time, while in the Sorbo DC large items take more time when located at the lowest and highest levels. It is possible that the effect of large items in the Yamaha DC was not confirmed due to a lack of observations of large items. In addition, it is possible that in the Yamaha DC, the higher level of the racks may have accounted for pickers taking more time in retrieving small items which need to be searched for before grabbing. Finally, it is worth noting that although the quantity is important in estimating cycle time, it is not very relevant for location decisions as only a moderate interaction effect was found in the case of the Sorbo DC.

### 5.2.2 Discomfort rating prediction model

#### Data collection

In this section we provide a measure for overall discomfort based on Borg's CR-10 scale (Borg, 1982; Dul et al., 1994). The scale combines desirable ratio and categorical properties by assigning labels for values from 0 to 10. In this way, 0 stands for no discomfort at all, 2 for weak discomfort, 3 for moderate discomfort, 5 for strong discomfort and 10 for the maximum discomfort, which requires the person to immediately stop the work activity. Values can be obtained from direct feedback of the workers on the job.

Data were collected during two days in each warehouse, observing each employee for only one day. In the case of the Yamaha DC, data for 5 employees were collected. In the case of the Sorbo DC, data for 7 employees were collected. For each employee a minimum of 40 observations were obtained. The randomly selected pickers were asked to rate their discomfort for each pick by telling their Borg scale rating directly to an evaluator who records the rating. This procedure has several advantages. First, the picker can concentrate fully on his task without having to write down the ratings himself which would interfere with a normal workflow. Second, the picker is urged to state his rating immediately, thus avoiding any ex-post rationalizations of his rating and enhancing the recall his physical picking experience.

The evaluator recording the ratings also recorded a number of other aspects. First, he recorded the level at which the item was picked. Second, the evaluator estimated if the item was of moderately high-volume ($MV$) or high-volume ($HV$). Products are considered of moderately high-volume if the volume is between 1 dm$^3$ and 5 dm$^3$ and of high-volume if the volume is greater than 5 dm$^3$. Thirdly, it was recorded whether more than 3 units ($MQ$) or 7 units ($HQ$) were picked in a single orderline. Heavy products ($HM$), having a mass over 3 kg, were identified by the pickers themselves and communicated to the evaluator who checks the actual weight of the pick. The reason why only ordinal data is collected, is because of the lack of time between picks to allow registration of precise characteristics of the items.

To control for differences in evaluating ratings, due to personal traits (including mood, sensitivity to discomfort), we also controlled for individual differences. We included a number of dummy variables (the number of participants minus one) to account for individual differences. These dummy variables are denoted by $E^{(r)}$ where $r$ is the identifier of the employee such that $r \in R$, and $r^*$ is the individual employee taken as reference.

To predict the discomfort rating for a product picked at a certain location, we use a similar formulation as was used for predicting the cycle time, assuming parsimony, we estimate a linear relationship with main effects where $b_1$, $b_2$, $b_3$, $b_4$, $b_5$ and $b_6$ are the linear coefficients to be estimated. This information is the same for both warehouses.

$$\begin{aligned} D^Y = b_0 + \sum_{k \in K, k \neq k^*} \alpha^{(k)} L^{(k)} + b_1 HM + b_2 MV + b_3 HV + b_4 MQ + b_5 HQ + \sum_{r \in R, r \neq R^*} b_6 E^{(r)} \\ + IND + \varepsilon \end{aligned} \tag{5.9}$$

The term $IND$ allows for possible interaction effects with picking at different levels and assumes that the nature of such interactions is linear with coefficients $\beta^{(k)}$, $\gamma^{(k)}$, $\lambda^{(k)}$, $\eta^{(k)}$ and $\zeta^{(k)}$ to be estimated. The term $IND$ is given by:

$$\begin{aligned} IND = HM \sum_{k \in K, k \neq k^*} \beta^{(k)} L^{(k)} + MV \sum_{k \in K, k \neq k^*} \gamma^{(k)} L^{(k)} + HV \sum_{k \in K, k \neq k^*} \lambda^{(k)} L^{(k)} \\ + MQ \sum_{k \in K, k \neq k^*} \eta^{(k)} L^{(k)} + HQ \sum_{k \in K, k \neq k^*} \zeta^{(k)} L^{(k)} \end{aligned} \tag{5.10}$$

Table 5.4: Empirical discomfort model for Yamaha DC and Sorbo DC.

| | Yamaha DC | | Sorbo DC | |
|---|---|---|---|---|
| Variables | b | Std. error. | b | Std. error. |
| (Intercept) | 1.595*** | 0.167 | 1.880*** | 0.150 |
| $L^{(1)}$ | 1.274*** | 0.338 | 0.722*** | 0.169 |
| $L^{(3)}$ | 1.176** | 0.336 | 0.842*** | 0.176 |
| $HM$ | 2.965* | 1.427 | 1.171** | 0.390 |
| $MV$ | 0.335 | 0.348 | 1.046*** | 0.365 |
| $HV$ | -0.175 | 0.802 | 3.286*** | 0.390 |
| $MQ$ | 2.008*** | 0.533 | 1.161*** | 0.189 |
| $HQ$ | 1.773** | 0.550 | 2.143*** | 0.333 |
| $HM * L^{(1)}$ | 2.059 | 2.332 | 1.075* | 0.476 |
| $HM * L^{(3)}$ | -0.974 | 1.758 | 0.395 | 0.443 |
| $n$ | 235 | -.- | 749 | -.- |
| $R^2$ | 0.279 | -.- | 0.311 | -.- |

Significance levels: $p \leq 0.05(^*)$, $p \leq 0.01(^{**})$, $p \leq 0.001(^{***})$.
Time given in seconds.

### Statistical analysis

The analysis of discomfort ratings using ordinary least squares is given in Table 5.4. Picking from different levels, picking heavy items and picking several units of the same item have a significant effect on discomfort levels. The magnitude of the effect is different though for both warehouses. Only for the Sorbo DC do the data confirm that the size of the product has an effect on discomfort. One possible reason why we do not find this for the Yamaha DC may be that we only have relatively few observations (49) in which we observe picks of medium or high volume. Similarly, for the interaction effects, we only find significant effects between picking levels and heavy masses and only in the case of the Sorbo DC.

The dummy variables we introduced for controlling individual differences do not influence the results significantly. For this reason and for the sake of conciseness, we report the results omitting the dummy variables of individuals even though these variables were included in the model. Besides, there appears to be a certain consistency among pickers concerning discomfort as evidenced by the high significance of the effects. All these facts suggest that pickers recognize differences in discomfort given different picking levels and masses, and are conscious of uncomfortable positions if asked directly.

In addition, it is interesting to note that the main effects point in the same direction for the estimation of discomfort ratings and cycle times. This suggests that improvements in one of the objectives may coincide with improvements in the other objective. However, given the different magnitude of the results a trade-off between objectives may also be possible. This will be investigated through the use of a multi-objective optimization model presented in the next section.

## 5.3 Storage assignment multi-objective model

### 5.3.1 Model formulation

The proposed model is a multi-objective optimization model with two objectives. The first objective is economical and concerns the minimization of the expected cycle time of picking operations. The second objective is social and entails the minimization of the expected average discomfort rating for retrieving actions. We are interested in obtaining a set of non-dominated solutions that can provide an idea about the trade-offs that a decision maker faces when determining storage locations for items within a particular zone in a warehouse.

To formulate the model we first define the following:

Sets

| | | |
|---|---|---|
| $I$ | : | the set of all items to be stored. |
| $J$ | : | the set of all possible storage locations. |

Variables

| | | |
|---|---|---|
| $x_{ij}$ | : | 1, if item $i$ is stored at location $j$; 0 otherwise. |

Model parameters

| | | |
|---|---|---|
| $D_{ij}$ | : | is a function that assigns for each possible combination of items and storage locations $(i, j) \in I \times J$ , an expected discomfort measure such that $D_{ij} \in [0, 10]$. |
| $CT_{ij}$ | : | is a function that assigns for each possible combination of items and locations $(i, j) \in I \times J$ an expected cycle time. |
| $p_i$ | : | probability that whenever there is a pick, the item picked is $i \in I$. |

We can now formulate the problem as follows:

$$z_1 = \min \sum_{j \in J} \sum_{i \in I} CT_{ij} x_{ij} p_i \tag{5.11}$$

$$z_2 = \min \sum_{j \in J} \sum_{i \in I} D_{ij} x_{ij} p_i \tag{5.12}$$

s.t.

$$\sum_{i \in I} x_{ij} \leq 1 \qquad \forall j \in J \tag{5.13}$$

$$\sum_{j \in J} x_{ij} = 1 \qquad \forall i \in I \tag{5.14}$$

$$x_{ij} \in \{0, 1\} \qquad \forall i \in I, \forall j \in J \tag{5.15}$$

The economic objective (5.11) minimizes the expected cycle time by multiplying the respective cycle times of a given item in a given location by the probability that such item is picked. To obtain the cycle time $CT_{ij}$ for the specific cases of the Yamaha DC and the Sorbo DC we used equations (5.7) and (5.9) with the corresponding coefficients estimated using the M-robust estimation method found in Tables 5.2 and 5.3 for the Yamaha DC and the Sorbo DC respectively.

Analogously, the social objective (5.12) minimizes the expected average discomfort rating by multiplying the respective discomfort rating of a given location-item combination by the probability that such an item is picked. To obtain the discomfort rating $D_{ij}$ for each product-location combination we used expression (5.9) with the coefficients found via the ordinary least-squares regression method displayed in Table 5.4.

Constraints (5.13) require that at most one type of item can be stored in a single storage position. Constraints (5.14) require that every item be assigned to only one location. From both constraints it can be inferred that we implicitly assume that there must be at least as many locations as items to be located, $|I| = \sum_{j \in J} \sum_{i \in I} x_{ij} \leq |J|$, otherwise the model would be infeasible.

### 5.3.2 Model solution approach

The bi-objective assignment problem is known to be $\mathcal{NP}$-complete (Ehrgott 2000). However, when considering only one objective, the problem reduces to a classical assignment problem which can be solved in polynomial time using the well-known Kuhn-Munkres algorithm (Munkres 1957). We are interested in the existence of any trade-offs between both objectives. We therefore use several convex combinations of both objectives to obtain supported non-dominated solutions (Ehrgott 2000), which are representative of the efficient frontier. We summarize our approach in the following steps.

1. Obtain an estimate for the cycle time and discomfort rating for every location-product pair by means of the formulas presented in Section 5.2.
2. Standardize the cycle times and discomfort ratings obtained in step 1 by subtracting the average of the estimated cycle times and discomfort rating from each estimated value and dividing this result by the standard deviation of the estimated values.
3. Choose a value of $\alpha$ in the range $\alpha \in [0, 1]$ to combine both goals $z = \alpha z_1 + (1 - \alpha) z_2$ and assign a single penalty for every location-product pair as a result of the combination of both objectives.
4. Avoid negative assignment cost values by adding the minimum of the standardized cycle times and discomfort ratings obtained to all standardized values.
5. Solve the resulting single-assignment problem.
6. Track back the selected assignments to obtain the actual average cycle time and average discomfort time of the non-dominated result obtained in Step 5.

Note that we apply, in step 2, a standardization procedure to bring the scales for the two goals to the same order of magnitude. This step is just to facilitate the selection of values for $\alpha$ while exploring the efficient frontier. We also apply step 4 to avoid negative assignment cost values not allowed when solving the Kuhn-Murkes algorithm.

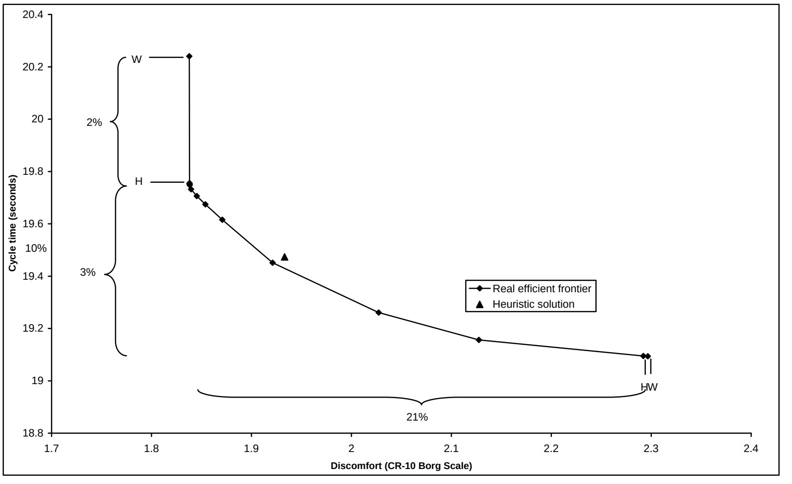



Figure 5.2: Efficient frontier of economic and social goals at Yamaha DC.

### 5.3.3 Model results

Figures 5.2 and 5.3 show the efficient frontier for zones at the Yamaha DC and Sorbo DC in the bi-objective assignment problem. As the total number of SKUs is larger than the number of locations in one zone, we preselected the SKUs randomly from the assortment list of each warehouse. The random selection was repeated six times for each warehouse, each time we solved the resulting bi-objective problem. Note that also in practice, when determining which SKUs should be allocated to each zone, random assignments are used to balance the stations' workload. Six trade-off curves were constructed for each warehouse and then these were summarized by averaging the six non-dominated solutions obtained for each selected $\alpha$ value. Figures 5.2 and 5.3 show the average efficient curve for each typical zone of a warehouse. It must be noted that the shape of each of the six curves was similar, displaying only shifting effects between them.

Each figure shows two dominated solutions indicated by a "W" that correspond to the worst case of solving a single objective assignment problem by considering only the economic or the social criterion. In addition, we also included a hierarchical solution approach marked with an "H" in which we first optimize for one criterion and then we choose, among the obtained optimal solutions, the one yielding the best performance for the other criterion.

The first important observation is that significant improvements can be made by optimizing hierarchically. Using this approach, between 2 to 5% in picking time can be saved for both warehouses by choosing the solution that yields the minimum cycle time from among the solutions that yield the lowest possible average discomfort. When we use the hierarchical approach, but optimize for cycle time first, we obtain a 4% improvement in terms of discomfort for the Sorbo DC, while for the Yamaha DC only a less than 0.5% improvement can be obtained.

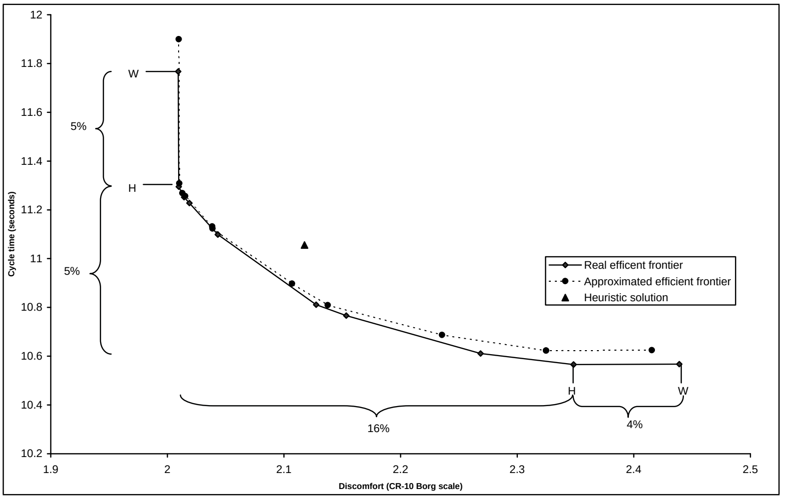



Figure 5.3: Efficient frontier of economic and social goals at Sorbo DC.

This shows to some extent that improvements in the second criterion can be obtained while keeping the first criterion at its optimal value. This implies that discomfort improvements are possible at no economic cost. Conversely, when giving priority to employees' well-being, efficiency improvements are possible while maintaining a maximum quality of working conditions. This also implies that optimizing *only* for the discomfort of employees is not advisable as the worst case scenario can yield results with significantly higher economical costs.

A decision maker may also decide to select an intermediate non-dominated solution. As can be easily seen in Figure 2, for the case of the Yamaha DC the trade-offs between discomfort and cycle time are only slight; 21% of improvement in discomfort costs only 3% of cycle time. This means that better values for discomfort can be obtained at fairly low costs with regard to cycle time. At the Sorbo DC a potential improvement of 5% in picking cycle time has to be traded off against an improvement of 16% in terms of discomfort ratings. It must be noted that these numbers reflect the shape of the efficient frontier. In many cases a warehouse may actually be operating at a point above and to the right of the curve. Starting from such a situation, initially large savings are possible for both goals simultaneously. Only once the efficient frontier has been reached, will trade-offs between cycle time and discomfort arise. Our model can aid in reaching the efficient frontier in the first place. Then after identifying the frontier, the model can be used to give insights about the trade-offs, which can be minor, as we found for the Yamaha DC, or moderately significant, as we found for the Sorbo DC. Without the model, a warehouse may be able to measure the current status of discomfort and cycle times, but it would not be possible to predict the effects of a reconfiguration on both aspects simultaneously.

Table 5.5: Empirical studies summary: a comparison of relative importance of location factors.

| | | Yamaha DC | | | | Sorbo DC | | | |
|---|---|---|---|---|---|---|---|---|---|
| Factor | Factor | Cycle Time | | Discomfort | | Cycle Time | | Discomfort | |
| Category | | Std. Coef. | Imp. | Std. Coef. | Imp. | Std. Coef. | Imp. | Std. Coef. | Imp. |
| 2D location | $MA$ | $0.134^{***}$ | P | -.- | n.a. | $0.423^{***}$ | P | -.- | n.a. |
| 2D location | $CA$ | $0.435^{***}$ | P | -.- | n.a. | -.- | n.a. | -.- | n.a. |
| 2D location | $CN$ | $0.198^{***}$ | P | -.- | n.a. | -.- | n.a. | -.- | n.a. |
| Level | $L^{(1)}$ | $0.058^{***}$ | S | $0.225^{***}$ | P | 0.006 | n.s. | $0.176^{***}$ | P |
| Level | $L^{(3)}$ | $0.019^{***}$ | S | $0.211^{**}$ | P | $0.008^{*}$ | S | $0.197^{***}$ | P |
| Interaction | $LV * L^{(1)}$ | 0.007 | n.s. | -.- | n.s. | -0.008 | n.s. | -.- | n.s. |
| Interaction | $LV * L^{(3)}$ | $0.072^{***}$ | S | -.- | n.s. | 0.013 | n.s. | -.- | n.s. |
| Interaction | $HV * L^{(1)}$ | 0.012 | n.s. | -.- | n.s. | $0.029^{***}$ | S | -.- | n.s. |
| Interaction | $HV * L^{(3)}$ | -0.016 | n.s. | -.- | n.s. | $0.028^{***}$ | S | -.- | n.s. |
| Interaction | $(Q-1) * L^{(1)}$ | $0.022^{***}$ | | -.- | n.s. | $-0.019^{*}$ | S | -.- | n.s. |
| Interaction | $(Q-1) * L^{(3)}$ | 0.005 | n.s. | -.- | n.s. | 0.004 | n.s. | -.- | n.s. |
| Interaction | $HM * L^{(1)}$ | -.- | n.s. | 0.061 | n.s. | -.- | n.s. | $0.123^{*}$ | P |
| Interaction | $HM * L^{(3)}$ | -.- | n.s. | -0.064 | n.s. | -.- | n.s. | 0.037 | n.s. |

Importance: P: Primary, S: Secondary, n.a.: not applicable. n.s.: not significant
Significance levels: $p \leq 0.05(^{*})$, $p \leq 0.01(^{**})$, $p \leq 0.001(^{***})$. Time given in seconds.

### 5.3.4 Model validation

The empirical results of Section 5.2 show that many factors work similarly for cycle time and discomfort at both Yamaha DC and the Sorbo DC. In Table 5.5 we summarize the findings of Section 2 classifying the relative importance of each location factor category by using the standardized coefficients obtained in the empirical investigations (the robust regressions for cycle time estimation models) and comparing their order of magnitude. The standardized coefficients are obtained by estimating the same model as in Tables 5.2, 5.3, 5.4 over the standardized values of the observations from the data sets. Note that for the cycle time, we again use the robust regression estimation method. The relative importance of the location and product factors for explaining cycle time and discomfort is consistent across the warehouses studied. This is surprising as these cases were selected for differences in product characteristics (see Section 5.2). Hence, we hypothesize that the location factors' relative importance hierarchy may hold more generally.

To test the robustness of the empirical relationships we used the Yamaha DC empirical Equation (5.7) and (5.9) to estimate cycle times and discomfort for the Sorbo DC for each item-location combination. We then plugged these values into the bi-objective function and solved the corresponding assignment problem. The resulting non-dominated solutions are presented in Figure 5.3 with a dotted line. It is apparent that the result is very close to the actual efficient frontier. This similarity strongly suggests that the relative importance of the cycle time and discomfort determinants is similar for both warehouses. We then hypothesize that for conventional warehouses with picker-to-part systems, our results may be generalizable as we expect a similar relative importance between walking and retrieving activities (in terms of cycle time). We note that we applied the Yamaha DC empirical relationships for analyzing the Sorbo DC and not the reverse as the Yamaha DC has a more general layout than the Sorbo DC.

One of the possible drawbacks of the proposed methodology is that it is a data intensive approach. Given that there is a potential for generalization, we propose a simpler heuristic procedure based on the empirical relationships obtained and the trade-off analysis results. The procedure only requires basic knowledge about the items and locations at hand. To construct such a procedure we use the ranking of the relative importance of the location factors obtained as given in Table 5.5. For simplicity and generalizability, we select only those factors that have been rated of primary importance either for cycle time or discomfort for both warehouses. Interaction factors were found to be of only secondary importance. As a result we propose the following simple heuristic that combines the two criteria and the popularity of a SKU:

1. Rank every location according to its 2D distance. Allow for ties in the case of locations in the same section (i.e. a whole column of locations).

2. Assign locations in the "Golden Zone" a rank of 1 and locations outside the "Golden Zone" a rank of 2.

3. For every rank at steps 1 and 2, divide the rank by the maximum rank obtained for each step. Next, sum both ratios (for steps 1 and 2) to obtain a location score.

4. Sort the location scores in ascending order. Then, sort items in descending order popularity and then assign the most popular items to the locations with the lowest scores.

The heuristic is constructed on the rationale that locationfactors are the most important and that relative walking distance and height should have equal weight in order to balance economic and discomfort considerations. This is because for reducing cycle time purposes, walking distance is the dominant factor, while for reducing discomfort, picking heights is the dominant factor.

Figure 5.2 and 5.3 show the dominated solution that this proposed heuristic yields, indicated by the label "Heuristic Solution". Although the heuristic solutions are dominated, these are close to the set of non-dominated solutions for practical purposes. Hence, for the cases studied we find that the proposed method resulted in "adequate" cycle time and discomfort levels. We caution that this method is designed based on the cases studied and therefore is particularly tailored to picking from shelves in environments where most of the picks involve only one orderline. We expect that for multiple orderlines per pick the trade-off between minimizing cycle times and discomfort would be less significant as pickers are forced to travel to further picking locations and hence there are more "Golden Zone" positions available at still relatively good 2D locations. It is clear that the trade-off analysis and the proposed allocation procedure should be further tested in similar and different order picking contexts.

## 5.4 Conclusions

This chapter presents a method for storage allocation decisions in the context of order picking from shelves. In particular, this method goes further than current storage allocation decision models in two main respects. First, we explicitly model the effect of location factors on cycle time using actual data. Second, we introduce the new criterion of improving the workers' well-being by minimizing their discomfort. Our method highlights the value of data stored in warehouse management systems. Furthermore, it shows that direct inquiry to pickers about their level of discomfort is an effective way of determining their preferences.

From the empirical studies, we find that the empirical relations obtained in both warehouses are similar in terms of the relative importance of each factor in predicting cycle times and discomfort. Such similarity, suggests that the relationships for predicting cycle time and discomfort are robust. Moreover, we find a certain degree of commonality between the determinants of cycle time and discomfort. As a result, only moderate trade-offs between the economic goal of minimizing cycle time and the well-being goal of minimizing discomfort were found.

From the trade-off analysis we conclude that optimizing only for discomfort may be a costly option in terms of increased cycle time and is thus not advisable. We also observe that the decision maker can improve both goals simultaneously until the solution reaches the efficient frontier where he is forced to make a decision whether or not to sacrifice some cycle time for the sake of decreasing discomfort. Hence, it is quite possible that a majority of firms that are not in the efficient frontier may gain economic benefits and be able at the same time to care more for the well-being of their employees when making storage assignment decisions.

Finally, based on the robustness of the empirical results we propose a heuristic procedure which has the advantage that it does not require knowledge of the specific empirical relationships to estimate cycle time and discomfort in a picking area. The procedure proved to be competitive in the cases studied by identifying points in the efficient frontier. However, more testing is recommended in similar and other contexts.

# Chapter 6

# Conclusions

## 6.1 Introduction

In an article celebrating five decades of operations management, it was noted that "no good manager would ignore the social dimension of the operating system" (Chopra et al, 2004). By extension, the field of operations management requires to continuously study relevant behavior of the people within an operating system. Acknowledging that fact, this thesis has addressed the problem of how to incorporate insights from the behavioral and ergonomic sciences in operational management models whenever workers are involved. Although, the scope of this thesis was restricted to routine, repetitive work, this scope alone proved to be more than ample for one thesis. Nevertheless, this thesis has served to initiate a systematic treatment of this subject, acknowledging previous work and exploring new ways in which operations management models may account for relevant human factors.

## 6.2 Key findings

To address the incorporation of relevant knowledge about workers in operations management models, this thesis has taken both a general and a specific perspective. Both perspectives have been necessary to the study of workers' involvement in operations management models. The general perspective served the purpose of providing an overview of the current state of the art, limitations and opportunities at the interface of human factors and operations management. The specific perspective on the other hand, allowed an in-depth study of specific human factors that can be influenced by operations management variables and that can simultaneously impact individual performance and job satisfaction.

This thesis started with the general perspective of Chapter 2, we found that there is value in integrating dispersed knowledge from the behavioral and ergonomic sciences within a framework for the purpose of making better informed operations management decisions regarding workers.

In this way, Chapter 2 identified and documented relationships between human factors and individual performance as well as job satisfaction. These relationships were evaluated in terms of how specific these are characterized and how much consensus there is among them. In particular, we found that relationships linking skill learning, skill forgetting, goal setting and fatigue with individual performance can be described in a mathematical way, albeit, with certain limitations. However, other factors including the use of incentives, peer pressure and feedback, are linked to individual performance, but are not characterized in sufficient detail to be able to transfer it into mathematical descriptions. Moreover, although contributing factors to job satisfaction have been identified, their relationships and interactions remain unclear. The need for more long-term longitudinal studies on contributing factors of job satisfaction is evident. Chapter 2, however, shows that only a sub-set of these contributing factors are important for operations management (see Figure 2.3).

Chapters 3 and 4, dealt, in-depth, with the subject of assigning production goals as an operations management tool to boost performance. We sought answers to two main questions in operations management contexts where workers are assigned a quantitative production goal to accomplish within a given period. First, we verified how performance varies with goal difficulty in operations management contexts. Second, we asked how do workers regulate their work pace under the influence of goals. In addition, in contrast to most studies of goal setting, workers are expected to work for the full assigned period with the desirable possibility of overreaching the goal. Furthermore, we review both questions considering the heterogeneity of results in work pace regulation and performance, such that individuals have different skill levels (i.e. a maximum capacity to perform the task).

In Chapter 3, we show that modeling work pace as a decision process is feasible and useful for generating testable hypotheses to answer the two questions presented above. Moreover, a framework of hypotheses, organized by assumptions, is created. In this way, we deduce that workers assumed to act myopically (i.e. considering only instantaneous desirability) behave differently than workers assumed to act after planning their work pace (i.e. considering the cumulative desirability for the whole period).

The laboratory study presented in Chapter 4, revealed evidence to support the assumption that individuals plan their effort. The laboratory study also verified one of the main results from the theory of goal setting by which performance increases with goal difficulty (level), but then levels-off constrained by the skill level. More importantly, a new result was obtained in work pace regulation. Challenging goals relative to the individual's ability induce steady-state work pace whereas non-challenging goals result in a decrease of the starting work pace with a slight acceleration towards the deadline and not the goal. In the cases of a non-challenging goal an acceleration towards the deadline was found instead of towards the goal as it has been previously reported in the literature. Furthermore, it was found that challenging goals also make work pace regulation patterns more predictable.

Finally, in Chapter 5 we conducted an empirical field study for the estimation of order picking cycle times and discomfort related to a given product and retrieval location. The empirical investigation was then followed up with a bi-objective assignment model where it is possible to estimate trade-off curves depicting non-dominated assignments for real warehouse cases. The empirical investigation showed a general agreement in both warehouses as to which location and product factors are important for estimating cycle times and discomfort. We also highlight the fact that the vertical position of the retrieval location was important for both, cycle time estimation and discomfort. As a result of such commonality, the analytical results showed a moderate trade-off between improving discomfort and improving cycle times. The results were also found to be robust and generalizable in similar order picking settings.

## 6.3 Contributions and implications for science

The studies presented in this thesis have direct implications at the interface of human factors and operations management. Although the vantage point of this thesis is from the field of operations management, the results of the studies in this thesis also have implications on the human factors fields. Overall, however, it is worth noting the diversity of research methodologies that this thesis makes use of in advancing knowledge at the interface of human factors and operations management: literature reviews studies, theoretical decision-making studies, laboratory studies, field studies and analytical trade-off studies. Such diversity in methodologies becomes a necessity to study complex of phenomena on the boundary of two fields. In the following lines we discuss the main implications for both academic fields of study.

Chapter 2's main contribution lies in integrating dispersed knowledge of worker specific factors and showing how such knowledge can be incorporated in operations management models. By centering the discussion on relationships that link operation management models with human factors, individual performance and job satisfaction, real progress can be made towards the inclusion of such considerations in operations management models. We do, however, limit our study to the inclusion of human factors that can be operationalized and that have an impact either on the feasibility or the optimality of operations management models. Applying such a relevance criterion is significant as it reduces the number of human factors that should be modeled.

In addition, Chapter 2 suggests that it is essential to advance empirical research on human factors relationships to incorporate worker specific relationships in operations management models. As empirical research defines relationships between human factors and operations, care should be taken that the operations management models are formulated in ways that are robust in changes of the relationships. For example, general functions that can be adapted for subsequent robustness analysis may be appropriate in handling uncertainties within the human factors relationships. An example of this strategy is given in Chapter 3 where a general assignment matrix assigning discomfort ratings to different product-locations pairs has the advantage that it can be adjusted with different estimation models.

From the results of goal setting studies in Chapter 3 and Chapter 4, our contribution is to challenge the assumption of operations management models that individual performance is independent of external factors (Boudreau, 2003)(Boudreau et al., 2003). For operations management models, our contribution is also to recognize that the assumption that workers work at stationary rates is only valid under the influence of goals if these are challenging enough. The findings described in the previous section regarding work pace regulation can be included within simulation models or even queuing models that commonly assume stationary work rates, reflecting more realistic dynamics under the influence of goals. Using these and other studies, goals may be included as new decision variables in operations models.

Another important contribution of the studies in Chapter 3 and 4 is that these are, to our knowledge, among the first studies that explicitly address the time dimension in goal setting. Most studies of industrial psychology in goal setting (Locke and Latham, 2005) test moderators together with goals, but have as the outcome total performance or overall satisfaction, ignoring any variation over time in terms of effort levels. The patterns of work pace regulation found in Chapter 3 and 4 show the value of longitudinal studies in discovering what the processes are involved when goals and deadlines are assigned. Time has indeed been recognized as one of the main dimensions in the field of motivation that still needs to be explored (Latham, 2006). The results of the studies in Chapter 3 and 4 should encourage further work on the dimension of time to gain a complete understanding of the dynamics of work regulation under an array of different circumstances (e.g. incentive pay, deadlines, feedback given).

Moreover, methodologically, the theoretical models in Chapter 3 show that developing decision making models have an unconventional value for theory building. The derivation of the properties of these models can provide testable hypotheses for further empirical work. Moreover, as decision models provide an internal logic with a set of assumptions, falsifying any of the hypotheses implies falsifying the entire decision model.

The study of storage location assignments presented in Chapter 5 contribute to a wider debate in the operations management field: Is the objective of well-being aligned with that of operational performance in operations management decisions? The methodology used in Chapter 5 to build an empirical model to serves as input for a trade-off model may be replicated to other operations management decisions where considerations of well-being and operational performance are important. An example of the application of this methodology may be in shift scheduling where the goal of cost effective schedules may not be completely aligned with that of cost-efficient schedules. An empirical investigation may identify the commonality of contributing factors related to work efficiency (performance measure) and fatigue (well-being measure). Such commonality is the basis for any alignment or conflict in both objectives. Next, an analytical model that uses the empirical study information can asses the commonality between both factors.

## 6.4 Implications for practice

Certain results of the studies of this thesis also have implications for operations management practitioners. While Chapter 2, is chiefly theoretical, it addresses a very pressing practical issue. Several operations management decision models have been dismissed by operations managers and planners on the basis that they are too unrealistic, dismissing important human factors. Such criticism can be unfounded. It is only when an interaction exists between the decision variables of a model and a worker-specific factor that the concern may be justified as shown in Chapter 2. Thus, the frameworks provided to interface the two distinct fields (i.e. human factors and operations management) helps to make operations management more applicable in real settings where the participation of workers is fundamental.

The results of the goal setting studies from Chapter 3 and 4 provide managers with confirmation that assigning goals are useful for boosting performance. Furthermore, for managers it makes sense to set challenging goals, even if these are beyond the skill level of a part of the population given that performance tends to level–off (but not decrease) when the skill level (capacity limit) is reached. In fact, managers have two extra reasons to assign challenging goals with deadlines as these induce steady state work rates and more reliable, predictable work rates. Furthermore, if managers want to identify if a goal is challenging enough to make workers work to the limits of their skill level, managers can verify the presence of a steady work pace. Additionally, in monitoring the progress towards the goal, managers may compare actual progress with previous patterns to predict if the goal can be attained or not within the deadline. Finally, in measuring the workers' satisfaction with their performance in terms of the goal, non-linear dynamics according to the "S–shape" function should be used, noting the increased sensitivity of "just missing the goal" by a narrow margin and the weak marginal gain in overreaching the goal.

For tactical storage location decisions, Chapter 5 provides a simple heuristic that can be used by warehouse managers and planners to obtain manual order picking systems that balance efficiency and comfort of their workers. The simple heuristic tested in Chapter 5 provided satisfactory solutions for economic and ergonomic objectives in the real warehouse cases studied. In addition, Chapter 5 also proved the value of using data commonly stored in warehouse management systems to have accurate and realistic (i.e. under normal operating conditions rather than artificial settings) of cycle time given retrieval locations and product characteristics. Despite the noisy data that may stem from this approach, the large number of varied observations and the use of appropriate outlier detection techniques makes such data a reliable source for cycle time estimation.

## 6.5 Future outlook

It is clear that research at the interface of operations management and worker-specific factors is still incipient. From the limitations and also the results of the studies presented in this thesis several questions arise. We highlight a few of these questions and end with a brief vision of what may be the future of operations management models for workers.

The review of worker related relationships present in Chapter 2 is limited to considering repetitive jobs. An account of the factors that are relevant for performance of more complex jobs with a lower degree of repetitiveness and more decision latitude of workers is still needed. Complex productive environments, such as in cell manufacturing or job shop manufacturing as well as planning and supervisory work, call for a review of other cognitive and social factors involved. These types of work not only involve simple decision making tasks which have been reviewed in a number of studies (see Gino and Pisano, 2008), but a broader set of tasks that need to be addressed. Already, for the example in Johnson et al. (2004) it was noted that production planning tasks have, in addition to decision making tasks, other types of sub–tasks (e.g. information gathering, relationship management) that have an important impact on the productivity of the planners.

The goal settings studies of Chapter 3 and 4 raise several questions in the context of operations management. One of the important questions is how goal assignments may function in more complex environments of operations management such as production lines. In production lines, Schultz et al. (2009) already document dependencies between workers and queue length. The question of how these dependencies interact with the effects of the individual (probably at the bottleneck level) and group goals assigned provides interesting research opportunities. For example, it may be interesting to investigate how the assignment of goals may interact with peer pressure in production lines. Furthermore, in production contexts where effort to produce is loosely linked to actual performance other questions emerge. Questions such as what would be the effectiveness of goals and how would work be regulated if the relationship between effort and performance is more stochastic or more ambiguous in nature as is the probable case with a broader set of more complex jobs. In addition, the issue of repeatedly assigning goals for coping with fluctuations in demand needs to be investigated from an empirical and operations management modeling perspective.

In addition, a study that explicitly addresses limitations of assigning goals in operations management contexts is still needed. Goals may induce higher immediate performance and steady work rates but this may come at the expense of decreasing quality, higher fatigue rates and possibly frustration for not achieving goals. These limitations of goals have not yet been explicitly studied in long term operations management contexts. Models may be constructed to identify what are the trade-offs between positive and negative effects of goals over a time horizon.

On the theoretical front, studies of goal setting raise other questions. For example, it is important to ask which stylized planning and controlling decision making model can parsimoniously explain all the work regulation patterns found in the empirical studies of Chapter 4 (i.e. steady work rate when challenging goals are assigned, selection of different initial work rates for different goals assigned, acceleration towards the deadline). Such a model will be suggestive of the mechanisms at play in work pace regulation and may be validated with further empirical tests, or even be used to predict performance of individuals.

In Chapter 5, the study is limited to specific order picking contexts with one retrieval per pick cycle. The extension of the study to other picking contexts such as contexts where more retrievals per cycle time exist as well as other contexts where for example, family grouping restrictions may apply to storage allocations (i.e. products that belong to certain families need to be allocated together). Moreover, as mentioned before, similar studies in other contexts where the aim is to identify the extent of trade-offs between classic operational performance objectives and well-being/job satisfaction related objectives are needed.

Finally, its is evident from this thesis that there exists several areas of future study at the interface of operations management and worker-specific factors and that these are important for a better understanding of the key actors in operations: the workers. However, these investigations should always consider the limitations of the study. From a theoretical point of view, not all effects of worker specific factors on performance and job satisfaction can, with the available knowledge, be sufficiently described for incorporation in operations management decision models. From a practical point of view, the effort of identifying or measuring the effects of worker specific factors may at times outweigh the benefits of doing so. Thus, the search for efficient ways of measuring such effects is a research subject of definite practical relevance.

# Summary

Within any added-value operations, for value adding activities to occur, people are required. Even in the case of automated systems, people act as operators and maintenance personnel. Operations research serves as support to the operations management field by developing decision-making models that assist in the choice of variables to optimize operations management performance. However, the emphasis of decision making models has traditionally been on the modeling of material and information flows. These models often consider people as indistinguishable from other types of resources such as equipment. By doing so, these models often disregard existing knowledge from behavioral and ergonomic sciences with the consequence that the feasibility and the objectives of these models may become compromised.

This disregard of results from the behavioral and ergonomic sciences has already been acknowledged in the operations management literature. Hence, the emergence of the field of behavioral operations; defined by Gino and Pisano (2008) as "the study of human behavior and cognition and their impacts on operating systems and processes". Nonetheless, even within such field there is a greater emphasis on bounded rationality and cognitive biases aspects that affect managers and planners in operations management functions, rather than on how decisions affect operational workers that in turn impact operating systems and processes.

In this thesis, we study the impact of operations management decisions on workers and subsequently on system performance. We refer to this subject as a sub-field in behavioral operations management: Behavioral Operations for Workers. Given the infancy of the field, this thesis has a two-fold approach. We first take a general approach where we propose a holistic framework for articulating both existing and possible future research on the field. Next, we take a case-specific approach where we investigate particular decisions of operations management that concern workers.

In Chapter 2, we take a general approach to the field of Behavioral Operations for Workers. Our goal is to review the existing knowledge that links operations management decisions with worker performance and worker job satisfaction with the objective of incorporating this in existing and potential operations management decision models. We propose a framework to identify relevant relationships between operations management variables and worker performance and job satisfaction variables. A review of the existing knowledge of worker specific factors that are prone to be influenced by operations management decisions clearly shows that knowledge is

available to be incorporated in current operations management models. However, it also shows that such knowledge is limited in the characterization of certain relationships between operations management variables with individual performance and job satisfaction. The limitations are particularly evident when the relationships deal with long-term effects. Thus, we show existing opportunities for modeling and empirical research in the field of Behavioral Operations for Workers. Moreover, we provide recommendations about how to incorporate state of the art knowledge of worker specific factors in operations management decision models, acknowledging at the same time current limitations of such knowledge.

Using the general modeling framework of Chapter 2, we focus our study in Chapters 3 and 4 on the use of setting specific quantitative production goals with a deadline for enhanced productivity. Both chapters attempt to answer two key questions for operations management: 1) What is the relationship between performance and goal level in operational contexts? 2) How do workers regulate their work-pace over time?

Chapter 3 focuses on generating hypotheses regarding possible answers for the aforementioned questions. The hypotheses are formulated by reviewing existing literature on the matter and proposing two alternative mathematical models that view workers as decision makers that select their work pace over time. Using a similar approach than the one used by behavioral economic models, two models are proposed. One model assumes that the worker is myopic and maximizes the instantaneous utility derived from a given work pace. The other model assumes that the worker plans and maximizes the total utility derived from the whole working period. In both cases, the utility is derived from the intrinsic desirability of a given work pace and by the extrinsic desirability of attaining a given level of performance with respect to an externally assigned goal.

The generated hypotheses from these models are then tested in Chapter 4 using a laboratory study. In the experiment, subjects have to perform a simple order picking task and the time between pick is recorded. We find from the experiments that a planning model with online revision of the plan is most consistent with our results. Further, in response to our original question we find that 1) performance tends to increase and level-off with and 2) challenging goals relative to the skill of the worker induce steady state work pace and more predictable work pace patterns. Moreover, only if the goal is perceived as relatively "easy" there exists acceleration towards the deadline and not towards the completion of the goal. We also show implications of these findings to the theory and practice of operations management.

Finally, in Chapter 5 we re-visit a classic operations management decision making problem: that of deciding on the location of items in a warehouse by including the perspective of the worker's well-being. The relevant aspect of well-being studied in this chapter is discomfort, a facet of job satisfaction identified in Chapter 2. In this study, we first perform an empirical field study in two existing warehouses to identify and quantify the location and product factors that impact the cycle time of order picking and also the discomfort felt by workers. The results of the empirical studies are then used as inputs for a bi-objective assignment problem that identifies the trade-off between storage location decisions that shorten cycle time and storage location decisions that diminish average discomfort of workers in picking. We find moderate trade-offs between both goals given commonalities in the factors that explain cycle-time and discomfort. The results imply that simultaneous improvements of both goals are possible in real-world situations before reaching the efficient frontier.

# Nederlandse Samenvatting (Summary in Dutch)

Mensen zijn altijd noodzakelijk voor de voortbrenging van goederen en diensten. Zelfs in het geval dat automatische systemen worden gebruikt, spelen mensen nog een onmisbare rol bij de bediening en als onderhoudsmonteurs. Het vakgebied Operations Management richt zich op het efficiënt en effectief maken van het voortbrengingsproces van goederen en diensten door gebruik te maken van onder andere technieken uit de Operations Research voor het maken van beslissingsmodellen. De nadruk van deze beslissingsmodellen is echter traditioneel gericht op het modelleren van problemen met relatief eenvoudig kwantificeerbare prestatiematen, zoals materiaal- en informatiestromen, machinecapaciteiten en machineplanning, locatie- en allocatieproblemen. Deze modellen beschouwen de mens vaak als ononderscheidenlijk van andere typen productiemiddelen zoals machines. Door deze aanpak wordt bestaande kennis uit de gedragswetenschappen en ergonomie vaak ter zijde gelegd met als gevolg dat de kwaliteit, oplosbaarheid of de doelstellingsfuncties van de modellen wordt aangetast, of dat soms belangrijke aspecten volledig buiten beschouwing worden gelaten.

Het feit dat resultaten uit de gedragswetenschappen en ergonomie niet worden gebruikt, is al eerder geconstateerd in de operations management literatuur. Daarom is het vakgebied "behavioral operationsöntstaan, welke gedefinieerd wordt door Gino and Pisano (2008) als het bestuderen van menselijk gedrag en cognitie en de invloed daarvan op operationele systemen en processen. Desalniettemin ligt zelfs in dit vakgebied de nadruk op aspecten van begrensde rationaliteit en cognitieve afwijkingen die van invloed zijn op managers en planners. Veel minder aandacht is er besteed aan de vraag hoe plannings- en ontwerpbeslissingen van invloed zijn op arbeiders en hoe dat vervolgens van invloed is op de prestaties van de operationele systemen en processen.

In dit proefschrift bestuderen we de invloed van karakteristieken van arbeiders op operations management beslissingen. We evalueren de invloed van operations management beslissingen op de arbeiders en de daarop volgende prestaties, we tonen aan hoe de karakteristieken van arbeiders opgenomen kunnen worden in operations management modellen, en laten zien hoe deze kennis benut kan worden om managementbeslissingen te verbeteren. Wij refereren aan dit onderwerp, zijnde een deelgebied van behavioral operations management, als Behavioral

Operations for Workers. Gegeven dat dit vakgebied nog in de kinderschoenen staat, kiezen we in dit proefschrift voor een tweeledige aanpak. Ten eerste kiezen we een brede aanpak waarin we een holistisch raamwerk voorstellen waarin zowel bestaand als mogelijk toekomstig onderzoek wordt benadrukt. Vervolgens volgen we een casus-specifieke aanpak waarin we bepaalde beslissingen van operations managers onderzoeken die invloed hebben op de arbeiders.

In Hoofdstuk 2 geven we een holistische benadering van het vakgebied Behavioral Operations for Workers. We geven een overzicht van de bestaande kennis die de operations management beslissingen verbindt met de prestaties van arbeiders en met de werktevredenheid van de arbeiders. Het doel is om veelbelovende mogelijkheden te identificeren voor het opnemen van deze kennis in bestaande en nieuwe beslissingsmodellen. Hiertoe stellen we een raamwerk voor dat relevante verbanden legt tussen operations management variabelen enerzijds en variabelen voor prestaties en tevredenheid van de arbeiders anderzijds. Deze evaluatie van bestaand wetenschappelijk onderzoek toont duidelijk dat kennis beschikbaar is van arbeiderspecifieke factoren voor opname in operations management modellen. Het toont echter ook dat deze kennis beperkt is tot de karakterisering van bepaalde verbanden tussen operations management variabelen en individuele prestaties of werktevredenheid. De beperkingen zijn vooral duidelijk wanneer het verbanden betreft met betrekking tot effecten op de lange termijn. Op deze wijze tonen we belangrijke kansen voor modelmatig en empirisch onderzoek op het terrein van Behavioral Operations for Workers. Bovendien voorzien we in aanbevelingen over de manier waarop de actuele kennis van arbeider-specifieke factoren kan worden opgenomen in operations management beslissingsmodellen, waarbij tegelijkertijd aandacht is voor de huidige beperkingen van deze kennis. Zo raden wij bijvoorbeeld aan om als doelstellingsfuncties in operationele modellen facetten van werktevredenheid op te nemen, die kunnen dienen als benadering van de feitelijke werktevredenheid. Deze aanbeveling is gebaseerd op het huidige beperkte empirische onderzoek, dat geen verklaring heeft voor de bijdragen van alle facetten van werktevredenheid en hoe deze samenkomen tot een algehele waardering van werktevredenheid. Gebruik makende van het algemene modelleerraamwerk van Hoofdstuk 2, richten we ons in Hoofdstukken 3 en 4 op het gebruik van situatiespecifieke kwantitatieve productiedoelen met een deadline ter bevordering van de productiviteit. Vanuit een Operations Management perspectief analyseren we "goal setting theory"; de theorie die analyseert hoe het beste taakdoelen kunnen worden gesteld voor het bereiken van individuele prestaties. Specifiek staan in beide hoofdstukken twee vragen centraal: 1) Wat is de relatie tussen prestatie en taakdoel in operationele omgevingen? 2) Hoe reguleren arbeiders hun werktempo door de tijd heen?

Hoofdstuk 3 richt zich op het genereren van hypotheses met betrekking tot mogelijke antwoorden op de voornoemde vragen. De hypotheses zijn geformuleerd op basis van een literatuurstudie en door het formuleren van wiskundige modellen waarin arbeiders worden opgevat als beslissers die door de tijd heen hun eigen werktempo kiezen. Gebruik makend van een vergelijkbare aanpak als in economische gedragsmodellen, creëerden we twee modellen. Een model is gebaseerd op de aanname dat de arbeider myopisch is en het onmiddellijke nut maximaliseert die volgt uit het werktempo. Het andere model volgt de aanname dat de arbeider vooruit kijkt en het totale nut maximaliseert over de gehele werkperiode. In beide gevallen is het nut samengesteld uit de intrinsieke wenselijkheid van een bepaald werktempo en de extrinsieke wenselijkheid van het bereiken van een bepaald prestatieniveau afgezet tegen het extern opgelegde taakdoel.

De in Hoofdstuk 3 geformuleerde hypotheses worden vervolgens in Hoofdstuk 4 gevalideerd door middel van een laboratoriumstudie. Bij dit experiment dienen de proefpersonen een eenvoudige orderverzameltaak uit te voeren waarbij de tijd tussen gepakte producten wordt geregistreerd. We zien in de experimenten dat een planningsmodel met online bijstellingen het meest overeenkomt met het daadwerkelijke gedrag van de proefpersonen. Bovendien vinden we in antwoord op onze oorspronkelijke vragen dat 1) de prestatie neigt te stijgen en daarna te stabiliseren bij stijgingen in het niveau van het taakdoel en 2) doelen die in verhouding tot de kundigheid van de arbeider uitdagend zijn, zorgen voor een stabiel werktempo en voor beter voorspelbare patronen in het werktempo. Bovendien is er uitsluitend bij als relatief ëenvoudig"gepercipieerde taakdoelen sprake van een toenemend werktempo bij het naderen van de deadline, niet bij het naderen van het taakdoel. We tonen ook de implicaties van deze uitkomsten voor de theorie en de praktijk van operations management.

Tenslotte keren we in Hoofdstuk 5 terug naar een klassiek operations management beslissingsprobleem, namelijk het bepalen van opslaglocaties voor producten in een magazijn met toevoeging van het perspectief van het welbevinden van de arbeiders. Het relevante aspect van welbevinden dat in dit hoofdstuk wordt bestudeerd, is "discomfort", een facet van werktevredenheid zoals geïdentificeerd in Hoofdstuk 2. In deze studie voeren we eerst een veldexperiment uit in twee bestaande magazijnen om locatie- en producteigenschappen te identificeren en kwantificeren die van invloed zijn op de cyclustijd van het orderverzamelen en ook op de mate van discomfort zoals gevoeld door de arbeiders. De resultaten van deze empirische studies worden vervolgens gebruikt als invoer voor een bi-objective toewijzingsprobleem dat de afweging identificeert tussen de opslaglocatiekeuzes die de cyclustijd verkorten en de opslaglocatiekeuzes die de gemiddelde discomfort van de arbeiders verminderen. We vinden gematigde belangenafwegingen tussen de twee doelen gegeven overeenkomsten in de factoren die de cyclustijd en discomfort verklaren. De resultaten impliceren dat gelijktijdige verbeteringen van beide doelen mogelijk zijn in de praktijk voordat de efficient frontier wordt bereikt.

Dit proefschrift richt zich op de analyse van nieuwe of zeer recente marketing gegevens. Hiertoe introduceren we een aantal nieuwe econometrische modellen. We presenteren modellen die nuttig zijn om het volgende te analyseren: (1) het optimale tijdstip voor de lancering van nieuwe en dominante technologieën, (2) de *triggers*, snelheid en de timing van een substantiële prijsverlaging voor nieuwe producten, (3) de heterogeniteit in preferenties van consumenten die leidt tot specifieke substitutiepatronen in geaggregeerde verkoopgegevens, en (4) locaties die een grote invloed hebben op de verspreiding van nieuwe technologieën. De econometrische technieken die we toepassen zijn divers, maar ze zijn voornamelijk gebaseerd op Bayesiaanse methoden. We maken gebruik van Bayesiaanse *mixture* modellen, Bayesiaanse variabele selectie technieken, Bayesiaanse *spatial* modellen en we introduceren een nieuwe Bayesiaanse benadering voor het random coëfficiënten logit model. De gegevens die we analyseren bestaan uit unieke en grote datasets. We bestuderen de prijzen van video-games, de verkopen van video-game consoles, de totale omzet voor specifieke consumentenproducten en online zoekgegevens van Google.

# Resumen en Español (Summary in Spanish)

En el proceso de la creación de bienes y servicios, el involucramiento de las personas es esencial. Incluso en el caso de sistemas automáticos de producción, las personas juegan un rol vital como operadores y personal de mantenimiento. El objetivo del área de la Administración de Operaciones es asegurar la producción eficiente y efectiva de bienes y servicios. El área utiliza, entre otras, técnicas de Investigación de Operaciones para desarrollar modelos de decisión. Sin embargo, el énfasis de los modelos de decisión ha sido tradicionalmente en problemas de modelación con medidas de rendimiento fácilmente cuantificables. Estos problemas fácilmente cuantificables incluyen problemas tales como los de flujo de material, de flujo de información, de capacidad y programación de equipos, de ubicación y de asignación de recursos. Estos modelos a veces consideran a las personas como indistinguibles de otros tipos de recursos como lo son las máquinas. Al hacerlo, algunos modelos existentes pueden ignorar interacciones entre las variables de decisión de los modelos y factores específicos de los trabajadores que son estudiados en las ciencias del comportamiento humano así como la ergonomía.

La no inclusión de resultados provenientes de las ciencias de comportamiento y ergonomía ya ha sido reconocida por la literatura de la Administración de Operaciones. Como respuesta a ello, ha surgido la nueva área de Operaciones del Comportamiento, definido por Gino y Pisano (2008) como el "estudio del comportamiento humano y sus procesos cognitivos así como sus impactos en los procesos y sistemas productivos". Sin embargo, incluso dentro de esta área, existe un énfasis en estudiar aspectos de racionalidad limitada y alteraciones cognitivas que afectan a los gerentes y personal de planeamiento. Menor atención ha sido prestada a dar respuesta a la pregunta de si las decisiones de planeamiento y de diseño de operaciones afectan a los trabajadores, y cómo a su vez ello afecta al rendimiento de los sistemas operacionales y sus procesos.

En la presente tesis, estudiamos el impacto de aspectos relativos a los trabajadores en decisiones de administración de operaciones. Evaluamos el impacto de decisiones de la administración de operaciones en los trabajadores y su desempeño en el trabajo. Asimismo, demostramos cómo aspectos de los trabajadores pueden ser incluidos en modelos de decisiones de operaciones y cómo el conocimiento de aspectos de los trabajadores pueden ser explotados para mejorar las decisiones en operaciones. Nos referimos al tema de incorporar aspectos relevantes de los traba-

jadores en modelos de decisión de operaciones como un sub-área del área de Administración de Operaciones como es la Administración de Operaciones Humanas para Trabajadores. Dado el estado incipiente de este campo académico, esta tesis hace uso de dos estrategias. La primera estrategia es general y propone un esquema holístico para articular las investigaciones del pasado y futuras en este campo. En el Capítulo 2, damos una visión holística del área de Administración de Operaciones Humanas para Trabajadores.

Asimismo, revisamos la literatura existente que conecta decisiones en la administración de operaciones con el rendimiento del trabajador y su satisfacción con su trabajo. El objetivo de esta revisión es el identificar oportunidades para incorporar este conocimiento en nuevos y existentes modelos de decisión. Para realizar este objetivo, proponemos un esquema que integra las relaciones que existen entre las variables de la administración de operaciones y las variables de rendimiento y de satisfacción de los trabajadores. La revisión de la literatura claramente demuestra que es posible incorporar conocimientos de factores humanos en los modelos de administración de operaciones. Sin embargo, al mismo tiempo, la revisión de la literatura demuestra que tales conocimientos están limitados en la caracterización de ciertas relaciones entre las variables de la Administración de Operaciones y las variables de rendimiento o satisfacción con el trabajo. Las limitaciones encontradas son particularmente evidentes con las relaciones que abordan efectos a largo plazo. A consecuencia de ello, identificamos oportunidades para realizar futuros estudios empíricos y de moldeamiento en el área de Administración de Operaciones Humanas para Trabajadores. Adicionalmente, proporcionamos recomendaciones de cómo incorporar conocimiento de factores humanos en modelos de decisión de la administración de operaciones considerando además las limitaciones del conocimiento actual. Por ejemplo, recomendamos incluir facetas de satisfacción con el trabajo como objetivos en modelos de operaciones ya que estas facetas pueden servir en reemplazo del concepto mismo de satisfacción con el trabajo. Esta recomendación está basada en que las actuales investigaciones empíricas están limitadas por no poder explicar cómo las facetas de satisfacción con el trabajo contribuyen y se integran en una sensación general de satisfacción con el trabajo. Utilizando el esquema general para modelar factores humanos del Capítulo 2, enfocamos nuestra investigación en los Capítulos 2 y 3 en estudiar la asignación de metas cuantitativas de producción dentro de plazos asignados con el fin de mejorar la productividad. Analizamos desde la perspectiva de la Administración de Operaciones la teoría que analiza la mejor manera de asignar metas para incrementar el rendimiento: La teoría de asignación de metas. En particular, ambos capítulos abordan dos preguntas relevantes para la teoría de administración de operaciones: 1) Cuál es la relación entre el rendimiento y el nivel de la meta en contextos operacionales? 2) Cómo los trabajadores regulan su velocidad de trabajo a través del tiempo. El Capítulo 3 se enfoca en generar una serie de hipótesis concernientes a las preguntas señaladas anteriormente. Las hipótesis son formuladas revisando la literatura existente y creando modelos matemáticos que abordan a los trabajadores como personas que toman decisiones seleccionando la velocidad a la cual realizan su trabajo. Usando un enfoque similar al utilizado en modelos de comportamiento económico, creamos dos modelos. El primer modelo asume que los trabajadores son miopes en sus decisiones y maximizan la utilidad instantánea obtenida al seleccionar un ritmo de trabajo. El otro modelo asume que el trabajador realiza planeamiento y maximiza la utilidad total obtenida de todo el tiempo disponible para trabajar. En ambos casos, la utilidad está compuesta de la preferencia intrínseca de seleccionar una velocidad de trabajo y la preferencia extrínseca de rendir a un cierto nivel con respecto a la meta asignada.

Las hipótesis formuladas en el Capítulo 3 son a continuación verificadas en el Capítulo 4 utilizando un estudio de laboratorio. En el laboratorio, los participantes del experimento deben realizar una tarea simple de consolidación de órdenes, típica de los almacenes y centros de distribución. Los resultados de los experimentos muestran consistencia con el modelo que asume planeamiento de parte de los trabajadores. Los resultados del experimento realizado dan respuesta a las interrogantes de investigación planteadas encontrando que: primero, el rendimiento tiende a incrementarse y luego nivelarse cuando se incrementa la meta asignada; y, segundo que las metas de producción que son percibidas como exigentes por los trabajadores tienden a inducir patrones de regulación de velocidad de trabajos constantes y más predecibles. Es más, solo si la meta de producción es percibida como relativamente "fácil", existe aceleración hacia el término del plazo asignado mas no hacia cuando la meta es completada. Adicionalmente, mostramos implicaciones de estos resultados para la práctica y teoría de la Administración de Operaciones.

Finalmente, en el Capítulo 5, revisamos un problema de decisión clásico en la Administración de Operaciones: el problema de decidir la ubicación de los productos en un almacén incorporando además la perspectiva del bienestar de los trabajadores involucrados. El aspecto relevante del bienestar de los trabajadores en este estudio es el malestar físico. Este aspecto es también una de las facetas de satisfacción con el trabajo identificadas en el Capítulo 2. En este estudio, primero realizamos un estudio empírico de campo en dos almacenes existentes, para identificar y cuantificar el impacto que tienen las variables de ubicación de producto y características del producto, en el tiempo de ciclo de órdenes de distribución así como en la sensación de malestar en los trabajadores. Los resultados del estudio empírico son luego utilizados en un problema de asignación con dos objetivos, que identifica el grado de alineamiento que existe entre el objetivo de minimizar tiempos de ciclo con el objetivo de minimizar la sensación de malestar de los trabajadores. Los resultados demuestran un grado de conflicto solo moderado entre ambos objetivos. Ello se debe a que existen factores en común que explican el tiempo de ciclo y el malestar de los trabajadores. Los resultados implican que es posible obtener mejoras en ambos objetivos en situaciones reales antes de llegar a la frontera eficiente de posibilidades.

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