Int. J. Production Economics 183 (2017) 194–207

Contents lists available at ScienceDirect

Int. J. Production Economics

journal homepage: www.elsevier.com/locate/ijpe

Balancing flexibility and inventory in workforce planning with learning

Silviya Valeva[a], Mike Hewitt[b], Barrett W. Thomas[c,*], Kenneth G. Brown[d]

[a] Applied Mathematical and Computational Sciences, University of Iowa, Iowa City, IA 52242, USA
[b] Information Systems and Operations Management, Quinlan School of Business, Loyola University Chicago, Chicago, IL 60611, USA
[c] Department of Management Sciences, Tippie College of Business, University of Iowa, Iowa City, IA 52242, USA
[d] Department of Management and Organizations, Tippie College of Business, Iowa City, IA 52242, USA

ARTICLE INFO

Keywords:
Workforce planning
Learning
Stochastic programming

ABSTRACT

We examine the problem of assigning workers to tasks, seeking to maximize profits, while taking in consideration learning through experience and stochasticity in demand. As quantitative descriptions of human learning are non-linear, we employ a reformulation technique that uses binary and continuous variables and linear constraints and is mathematically equivalent in nearly all cases. Similarly, as demand is not assumed to be known with certainty, we embed this mixed integer representation of how experience translates to productivity in a stochastic workforce assignment model. With an extensive computational study and analysis of (near-)optimal solutions, we demonstrate that modeling both learning and uncertainty in demand leads to improved task assignments. Furthermore, we formulate and test hypotheses based on these solutions that yield insights into how best to manage practice, cross training, and inventory. We show that cross training increases as demand uncertainty increases, worker practice increases as inventory holding costs increase, and workers with less initial experience receive more practice than workers with higher initial experience.

1. Introduction

The literature has long recognized that cross training can help organizations overcome the effects of demand variability. Yet, much of this literature is focused on identifying the cross-training configuration, the number of tasks on which each employee should be trained, and the skill pattern, the skills that should be grouped together for cross training (Hopp et al., 2004; Hopp and Van Oyen, 2004; Jordan and Graves, 1995). However, individuals in a workforce do not arrive cross trained. Rather, it is a process that happens over time, resulting from the deliberate assignment of workers to tasks and the proficiency that follows from experience gained in performing the tasks. While this learning-by-doing is well recognized, workforce planning models rarely consider it. As such, in this paper, we study how recognizing the improvement of productivity during a planning horizon can aid in making more impactful managerial decisions. Further, the literature that does consider learning ignores the impact that uncertainty in demands should have on decision making. As a result, in this paper, we present a two stage stochastic program wherein uncertainties in demands are modeled with scenarios.

Specifically, we seek to derive managerial insights about specialization versus cross training, influence of holding costs on task assignment decisions, and worker selection for different types of assignments in a production setting. We formulate hypotheses and test them with a computational study using a decision model that yields practical solutions by capturing both the realities of human learning and uncertainty in demand while seeking to maximize profits. In order to draw conclusions, we use a general production environment in which we presume that near-term demand is known with certainty but that later-term demand is not. The available workforce is assumed to consist of a team of individuals, recognized to differ in their experience, productivity, and learning. The model prescribes assignments on production lines, consisting of sequentially ordered tasks that yield finished goods, as illustrated in Fig. 1.

The quantitative description of human learning used in this paper takes the form of a non-linear function. As non-linear programs are still computationally difficult to solve, we use a reformulation technique to instead represent the impact of experience on productivity with binary and continuous variables and linear constraints. This mixed integer representation relies on an enumeration of potential experience levels, with experience measured in terms of past productivity. The reformulation is exact except in cases wherein workers are unable to perform at their maximum productivity because they are starved for work.

The contributions of this paper are in providing a validation for incorporating learning and stochasticity in assignment models, de-

* Corresponding author.
E-mail addresses: silviya-valeva@uiowa.edu (S. Valeva), mhewitt2@luc.edu (M. Hewitt), barrett-thomas@uiowa.edu (B.W. Thomas), kenneth-g-brown@uiowa.edu (K.G. Brown).

http://dx.doi.org/10.1016/j.ijpe.2016.10.026
Received 24 November 2015; Received in revised form 14 October 2016; Accepted 16 October 2016
Available online 06 November 2016
0925-5273/

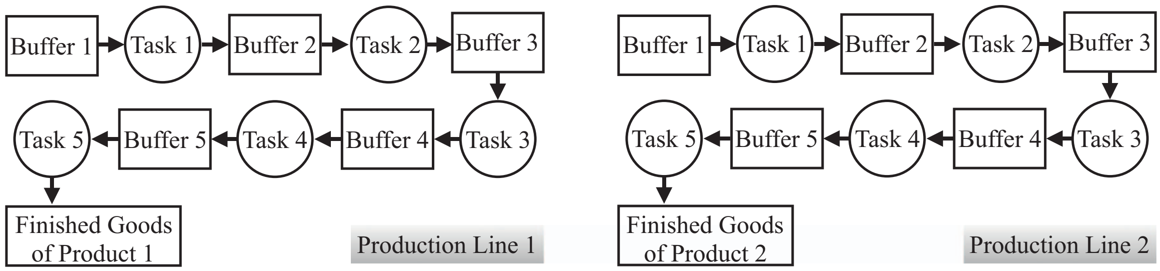

Fig. 1. Process configuration for two serial production lines.

monstrating that cross training can be used to hedge against uncertainty, and in offering insights into how workers should be assigned to tasks based on their individual differences in experience. Specifically, we design experiments to demonstrate the trade-offs between cross training and inventory and show that cross training increases as demand uncertainty increases, worker practice increases as inventory holding costs increase, and workers with less initial experience receive more practice than workers with higher initial experience. Additionally, in order to conduct those experiments, we introduce a linear reformulation of a stochastic workforce assignment problem with learning that is exact in nearly all cases.

The remainder of this paper is organized as follows. In Section 2, we review the relevant literature. Section 3 outlines the three hypotheses involving human learning that we seek to address. Section 4 describes the problem setting chosen for testing the hypotheses, the formal model, test instances, and analytical approach. Section 5 presents the computational results and analysis. Finally, Section 6 provides managerial insights, while Section 7 offers conclusions and suggestions for future work.

2. Literature review

The main relation of this work to the existing literature is in the explicit modeling of individual human learning and demand uncertainty, as well as in the managerial insights regarding cross training and practice. To the best of the authors' knowledge, few papers model both learning and stochasticity in demand, thus they are presented and reviewed separately. Furthermore, we review papers focusing on cross training that provide more insightful rather than methodological contributions.

2.1. Learning

Workforce variability governed by the inherently different human learning and forgetting rates has been incorporated in a number of recent works seeking to model and optimize production scheduling. However, most models are deterministic and do not consider stochasticity in demand. Wirojanagud et al. (2007) consider a model with a heterogeneous workforce in which workers have different skill sets. However, the model does not capture the continuous nature of learning and forgetting as a function of time and repetition. When training occurs, the worker's skill set, representing their ability to operate a given machine group, changes by adding new skills to the set. The authors seek to minimize workforce-related costs such as hiring, firing, training, and salary costs, while creating an optimal strategy to staff a job shop. The model is presented as a mixed integer program, which is computationally expensive for large instances. The computational burden of the model is addressed by Fowler et al. (2008) who develop two linear programming-based heuristics and a genetic algorithm to improve the computational time.

To account for learning and forgetting based on individual traits, several authors consider a specified concave performance function to model individual learning on the job. Corominas et al. (2010) propose a deterministic task assignment model seeking to minimize completion time of a series of tasks assigned to workers. A piecewise linear approximation to the learning function is used in the solution. Bentefouet and Nembhard (2011) explicitly model individual performance differences including learning behavior in both fixed assignment systems and work sharing systems, characterizing the optimal switching times when work sharing has productivity advantages. They show that the optimal strategy for maximizing the throughput from the least productive task depends on the workers' learning and productivity characteristics. Grosse and Glock (2015) review the impact that incorporating individual learning can have on order picking efficiency in a warehouse. The experimentation and numerical results demonstrate several benefits of modeling learning, including a better predictability of lead times, insights for strategic workforce allocation, and identification of factors facilitating learning.

Considering further the implications of modeling learning in assignment problems, Nembhard and Bentefouet (2014) test and analyze different strategies for worker selection based on learning and forgetting parameters, seeking to maximize throughput. The authors consider several cases with different ratios of specialists to generalists, levels of multifunctionality, describing the number of tasks a generalist needs to perform, and levels of workforce heterogeneity. By examining different worker ranking and selection policies, the authors seek to determine the degree to which those policies may be effective means of improving productivity. Introducing a new approach, Nembhard and Bentefouet (2015) model learning as both a direct process, through experience, and an indirect process, through transfer of knowledge between members of a team. They consider scheduling in three stages that consist of selecting workers, grouping in teams, and assigning workers to tasks, seeking to maximize throughput. Further applications of learning and forgetting in modeling workforce management are reviewed by Hewitt et al. (2015).

2.2. Demand uncertainty

A number of authors consider workforce planning under uncertainty using stochastic programming approaches. However, their work does not incorporate learning as a function of experience. Martel and Price (1981) model the case where manpower demands and available resources for future periods are not known with certainty as a multi-stage stochastic program, using Normal and Beta probability distributions. Zhu and Sherali (2009) present a workforce planning model to manage a multi-category workforce of different skill levels with several functional areas, each with capacity constraints and uncertain workforce demand. A workforce recruitment and allocation plan is made on a monthly basis, resulting in a two-stage stochastic program. While the workers in the model are different and classified in categories, there is no possibility of learning or switching of categories between workers. Fragniere et al. (2010) extend the stochastic programming version of the aggregate planning model to assess the level of human expertise necessary to deal with operations risks in the back offices of banks. Two categories of professionals are considered in a multistage stochastic program with extensions to account for demand, dependent on decisions. The authors propose as a future research the application of learning curves to the model to describe the employees' learning