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## Modeling and optimization control of a demand-driven, conveyor-serviced production station $\stackrel{\text{\tiny{$\Xi$}}}{\sim}$

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#### ABSTRACT

This study investigates the look-ahead control of a conveyor-serviced production station (CSPS), viewed as a production center, which is connected to a sales center. The production station is equipped with a buffer to temporarily store the parts that will flow into the product bank of the sales center after processing. The whole two-center system is characterized by random parts arrival, random customer demand, random processing time and limited buffer or bank capacities. Thus, the decision-making on the look-ahead range of such demand-driven CSPS is subject to the constraints of production and sales levels. In this paper, we will focus on modeling the stochastic control problem and providing solutions for finding the optimal look-ahead control policy under either average- or discounted-cost criteria. We first establish a detailed semi-Markov decision process for the look-ahead control of the demand-driven CSPS by combining the vacancies of both the buffer and the bank into one state, which can be solved by policy iteration or value iteration if the system parameters are known precisely. Then, to avoid the curse of dimensionality and modeling in the numerical optimization methods, we also propose a *Q*-learning algorithm combined with a simulated annealing technique to derive the approximate solutions. Simulation results are finally presented to show that by our established model and proposed optimization methods the system can achieve an optimal look-ahead control policy once the capacities of both the buffer and the bank are designed appropriately.

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#### 1. Introduction

In many real-world manufacturing enterprises, there is usually a type of production station situated along a constant-speed conveyor, by which some parts are randomly conveyed to the station for necessary processing. Generally, the station is equipped with a finitecapacity buffer to store temporarily the parts to improve flexibility. This production model is called a conveyor-serviced production station (CSPS), which originates from Ford's assembly line (Matsui, 1993, 2005, 2009). It can be viewed as an abstract model of present-day automated manufacturing processes such as robotic assembly lines

http://dx.doi.org/10.1016/j.ejor.2015.01.009 0377-2217/© 2015 Elsevier B.V. All rights reserved. (Matsui, 2009; Tang & Arai, 2009) and is usually associated with jobshop scheduling in real production (Matsui, 2009; Sadrzadeh, 2013; Zuo, Xue, Zhou, & Guo, 2013). In fact, as an intellectual production model, CSPS has received wide use in most world-famous and advanced enterprises, such as in the mobile-phone (LCD) assembly line of Fujitsu and the HDD production line of Toshiba. Therefore, the optimal control of such type of production model has practical significance and is an important issue in the field of industrial engineering.

For the control of this traditional single-station CSPS, Matsui has already established a semi-Markov decision processes (SMDP) model and given the calculation equations for some of the performance values (Matsui, 1993, 2005, 2009). He has also summarized all of the different control modes and given a physical theory on CSPS models (Matsui, 2005, 2009). Based on this work, Tang and Arai developed a potential-based online policy iteration for the optimal look-ahead control of this system (Tang & Arai, 2009). Among these studies, the production of the station is independent from the sale. Today, as an effect of economic development in the age of supply chain management (SCM), real-time production may be greatly influenced by the markets (Mikuriya & Nakade, 2013; Yamada, Satomi, & Matsui, 2006), which implies that the production scheduling of a production center

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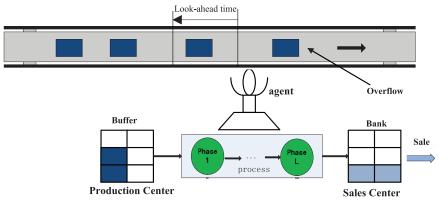


Fig. 1. Demand-driven conveyor serviced production station.

should be combined with the inventory management of a sales center under the circumstance of uncertain customer demands. So the related optimization control is becoming important and attractive in the SCM age. For instance, Ventura et al. presented a multi-period inventory lot-sizing model for a single product in a serial supply chain, where the demand is known and may change from period to period (Ventura, Valdebenito, & Golany, 2013). In addition, Ioannidis has considered a single-product and make-to-stock manufacturing system facing random demand from two customer classes with different quality cost and profit parameters (Ioannidis, 2013). Further, Hussain et al. proposed a probabilistic assessment of loss in revenue generation in demand-driven production (Hussain, Dillon, Hussain, & Chang, 2012) and Bertrand and Van Ooijen have studied the capacity investment decisions of make-to-order manufacturing firms where the demand rate can be controlled by increasing or decreasing their sales effort with a fixed capacity (Bertrand & Van Ooijen, 2012). Similarly, for modern production in many manufacturing industries, a CSPS viewed as a production center is sometimes connected to a sales center, which is equipped with a product bank to store the processed parts moved from the station and meet random customer demands. In previous studies related to traditional CSPS, the limitation of the bank capacity and the real-time inventory level are usually not considered (Matsui, 1993; Tang & Arai, 2009). In practice, the bank capacity is definitely finite and the customer demands may be stochastic, diverse and unpredicted, which will dynamically affect the inventory level and thereby, the production of the station. Thus, we term this two-center model as demand-driven CSPS that is obviously characterized by random parts arrival, random customer demands, random processing time and limited buffer or bank capacities. Therefore, coping with the model and the look-ahead control of the demand-driven CSPS is a key challenge and more complex than that of the traditional CSPS

So far, only a few studies of a demand-driven CSPS system have been carried out, although this production model is important in the context of SCM. It was first discussed in a job-shop model with order selection by Matsui (1988) and has been developed to a management game model (Matsui, 2002, 2009). In this paper, we consider the case of a demand-driven CSPS system with limited buffer and bank capacities, which is an extension of our previous work (Chen, Tang, Zhou, & Ma, 2010). Our goal is to formulate the system by a mathematic model and provide solutions to find an optimal or suboptimal lookahead control policy. In view of this and without loss of generality, we make some assumptions: (i) the conveyor runs at a constant speed; (ii) parts arrive at the production center in a Poisson process; (iii) customers also arrive at the sales center in a Poisson process that is independent of the parts arrival, and each customer takes one processed part away from the bank; and (iv) the time for unloading a part from conveyor to the buffer and the time for moving a processed part from the production center to the sales center are ignored. We first establish a detailed model of the demand-driven CSPS as a semi-Markov decision process (SMDP), which can be solved by policy iteration or value iteration if the system parameters are known precisely. Unlike traditional CSPS, vacancies of the buffer and the bank are jointed to be viewed as the system state, which implies that random customer demands are eventually taken into account to decide the look-ahead range of the production station. Due to the system complexity and especially the random dynamics, the numerical optimization methods will be subject to the so-called "curse of dimensionality" and "curse of modeling". Therefore, we also propose a model-free reinforcement learning method (i.e., Q-learning algorithm) to search for an optimal or suboptimal look-ahead control policy by introducing simulated annealing to construct the exploration scheme to avoid a local extreme.

The remainder of this paper is organized as follows: In Section 2, we describe the demand-driven CSPS system and establish its detailed SMDP model. In Section 3, we introduce the optimization solutions including numerical methods and reinforcement learning methods. We then provide some simulation results in Section 4, and conclude the paper with some brief comments in Section 5.

#### 2. Demand-driven CSPS and SMDP model

#### 2.1. Physical model

The physical model of a demand-driven CSPS is illustrated in Fig. 1 and introduced as a two-center model consisting of production and sales centers. The production center has a finite-capacity buffer storing the parts unloaded from the conveyor, and the sales center has a finite-capacity bank storing the processed parts moving from the production center and satisfying customer demands. The agent of the production center will dynamically judge if a part is arriving within a certain range along the conveyor and derive its location information such as the position and orientation. The look-ahead range is viewed as the control or decision variable. Because the conveyor runs at a constant speed, hereafter any range along the conveyor (e.g., the lookahead range) will be represented by units of time. The demand-driven CSPS works as follows: at a decision epoch, the agent will look ahead some range according to the current vacancies of both the buffer and the bank. If there is at least one part in the look-ahead range, the agent will wait until the first one arrives at the pickup position and then unload it into the buffer. Otherwise, he/she will immediately take one reserved part out of the buffer to process and during which time, all arriving parts will be lost; after the service is finished, the processed part will be moved into the bank of the sales center. Concurrently with either operation, customers arrive at the sales center randomly, and each customer will take one production away from the bank. In addition, we assume that if the bank is vacant, the customer will be lost.

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