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Procedia CIRP 57 (2016) 55 – 60

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49th CIRP Conference on Manufacturing Systems (CIRP-CMS 2016)

Optimized Adaptive Scheduling of a Manufacturing Process System with Multi-Skill Workforce and Multiple Machine Types: An Ontology-Based, Multi-Agent Reinforcement Learning Approach

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Abstract

The impetus for an interconnected, efficient, and adaptive manufacturing system, as advocated by the Industry 4.0 revolution, together with the latest developments in information technology, advanced manufacturing has become a prominent research topic in recent years. One critical aspect of advanced manufacturing is how to incorporate real-time demand information with a manufacturer's resource information, including workforce data and machine capacity and condition information, among others, to optimally schedule manufacturing processes with multiple objectives. In general, optimized manufacturing scheduling is a non-deterministic polynomial-time hard problem. Due to the complexity, scheduling presents a number of challenges to find the best possible solutions. This research proposes an ontology-based framework to formally represent a synchronized, station-based flow shop with a multi-skill workforce and multiple types of machines. Based on the ontology, this research develops a multi-agent reinforcement learning approach for the optimal scheduling of a manufacturing system of multi-stage processes for multiple types of products with various machines and a multi-skilled workforce. By employing a learning algorithm, this approach enables real-time cooperation between the workforce and the machines, and adaptively updates production schedules according to dynamically changing real-time events.

Peer-review under responsibility of the scientific committee of the 49th CIRP Conference on Manufacturing Systems

Keywords: scheduling; workforce management; reinforcement learning; multi-agent; multi-stage; multi-product; multi-skills; real-time information; advanced manufacturing; game theory

1. Introduction

Production scheduling is a very important and challenging problem in many manufacturing and process industries[1]. The development of information and automation technology and the impetus for optimized scheduling calls for a rigorous approach that incorporates real-time information to solve dynamic, stochastic environment, complex manufacturing scheduling problems[2].

Many studies have been conducted working toward scheduling-problem solutions[2]. However, few papers take both manufacturing system scheduling and workforce scheduling into consideration.

In this paper, we consider a manufacturing scheduling problem that is commonly encountered in various manufacturing factories. The manufacturing system is composed of manifold stages with multiple workstations producing multiple products[3], and with a workforce having different levels of skill[4–6] based on synchronized stations. In order to solve this dynamic scheduling problem within a stochastic environment, we develop a multi-agent system that consists of a human resource management agent and a manufacturing scheduling system agent. Based on the system, we construct Markov decision process (MDP) problems for each agent in order to solve them using appropriate computational learning approaches. More specifically, from a data-driven perspective, we present a multi-agent reinforcement, learning-based approach for dealing with a synchronized-station-based flow shop with a multi-skill workforce and multiple types of machines.

Peer-review under responsibility of the scientific committee of the 49th CIRP Conference on Manufacturing Systems
doi:10.1016/j.procir.2016.11.011

The paper is organized as follows. First, we describe an ontology-based framework to formally represent the system. We then construct two optimization problems for each agent by defining objective functions, constraints of employee scheduling, and the work of production scheduling agents. Next, we apply a multi-agent system with a reinforcement learning approach to compute optimal policy for the system according to real-time samples of the dynamic environment. Finally, we carry out numerical experiments to demonstrate the performance of this approach under static and dynamic environments and under different conditions of a flow shop. Through this study, we hope to shed light on how to design and implement optimized manufacturing scheduling under the realistic interactions between a workforce skill set and adaptive machines in a manufacturing environment—a topic that is of foremost importance for future advanced manufacturing.

2. Literature Review

Scheduling is a critical problem in manufacturing[2,7,8], and here, much work has been conducted. In the past, people have proposed heuristic methods to improve their production systems. Traditional methods, such as push systems (known as material requirement planning, or MRP) and pull system (known as just-in-time, or JIT) are two of the most important planning and scheduling approaches[8,10]. There have also been many studies attempting to solve scheduling problems from an analytical perspective, such as queuing theory[10].

Recently, some have started to try to solve the scheduling problem as an optimization problem. Different approaches, such as integer programming[11] and genetic algorithms[12], have been presented to solve scheduling problems under different scenarios[1,16]. For example, Ferris et al. developed a dynamic decomposition scheme that exploits the grid structure of a typical factory layout and customizes it for grid computing[1]. In addition, due to the complexity of manufacturing systems, some have proposed different ways to reduce computational costs[11], as well.

In the past few years, with the development of machine learning, the advancement of information technology, and the higher requirements for scheduling, many studies have been carried out from a dynamic perspective. Compared with static scheduling methods, these newer schemes incorporate environment information and adaptively reschedule according to different events[17–19].

In practice, most workstations are operated by manpower. However, the majority of past studies do not take this factor into consideration. Though there are many studies focused on employee and workforce scheduling, researchers have mainly focused on forecasting demands, staffing requirements, and optimal shift scheduling using different optimization algorithms[4,5,20,21] under various scenarios, such as a multi-skill workforce.

On the other hand, to the best of our knowledge, there have been relatively few studies on manufacturing scheduling combined with workforce scheduling. With the development of computer technology, we attempt to apply reinforcement learning and multi-agent methods to deal with this area.

3. Problem Formulation

Due to the complexity of a practical scheduling system, we build a multi-agent model to represent the manufacturing scheduling agent and the human resource management agent. Both agents have their own utility functions and constraints. In a real manufacturing environment, these two agents cooperate toward an efficient, cost-effective, and flexible manufacturing system. The manufacturing scheduling model is based on the idea of the synchronized station, which is similar to the centralized reinforcement learning approach and the batch scheduling model of a multi-stage process[1]. In this model, data about each product is tracked with an identity system, information regarding each individual worker is recorded and updated, and the working environment for each machine can be monitored and stored in a database. Therefore, both agents share all available information in an attempt to understand the whole mechanism of the system and to create optimal policies under different states according to their multiple objectives.

3.1. System Framework

The following is the nomenclature of the proposed system.

Nomenclature

t	Time step
pid	Product id
ty	Product type
Ty	All types of products
k	The k^{th} process
K	Total K processes
J_k	Number of machines at k^{th} process
p_{pid}	Product with *pid* product id
$pt_{ty,k}$	Average processing time of ty-type product at k^{th} process
$S_{ty.k}$	Setup time of ty-type product at k^{th} process machines
$m_{j,k}$	The j^{th} workstation at process k
M_k	The machine set at process k
$h_{j,k}$	The health information of the j^{th} machine at process k
H	Total number of categories of health information
b_k	The buffer that stores all wait in process at process k
F	The finished buffer
B	Buffer size
o_l	The l^{th} order
O	The order set
λ_{ty}	Parameter that describes the frequency of an order of ty-type product
u_{ty}	Unit price of a ty product
q_l	Amount of product in l^{th} order
R_l	Total reward for an order
c_l	Penalty of the overdue l^{th} order per time step
s_l	Starting time of the l^{th} order
d_l	Due time of the l^{th} order
id	Worker's id
w_{id}	A worker with an id
sk	Set of skills or machines a worker could operate
sl	Skill level