Robotics and Computer-Integrated Manufacturing ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Robotics and Computer-Integrated Manufacturing

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

Full length Article

Selection of cutting conditions for power constrained parallel machine scheduling

Yi-Chi Wang*, Ming-Jun Wang, Sung-Chi Lin

Department of Industrial Engineering and Systems Management, Feng Chia University, No.100, Wenhwa Road, Seatwen, Taichung, 40724, Taiwan

ARTICLE INFO

Article history:
Received 31 March 2015
Received in revised form
6 July 2015
Accepted 21 October 2015

Keywords:
Cutting conditions
Parallel machine scheduling
Power demand
Genetic algorithm

ABSTRACT

Most previous studies on machining optimization focused on aspects related to machining efficiency and economics, without accounting for environmental considerations. Higher cutting speed is usually desirable to maximize machining productivity, but this requires a high power load peak. In Taiwan, electricity prices rise sharply if instantaneous power demand exceeds contract capacity. Many studies over the previous decades have examined production scheduling problems. However, most such studies focused on well-defined jobs with known processing times. In addition, traditional sequencing and scheduling models focus primarily on economic objectives and largely disregard environmental issues raised by production scheduling problems. This study investigates a parallel machine scheduling problem for a manufacturing system with a bounded power demand peak. The challenge is to simultaneously determine proper cutting conditions for various jobs and assign them to machines for processing under the condition that power consumption never exceed the electricity load limit. A two-stage heuristic approach is proposed to solve the parallel machine scheduling problem with the goal of minimizing makespan. The heuristic performance is tested by distributing 20 jobs over 3 machines with four possible cutting parameter settings.

1. Introduction

Climate change has emerged as a critical challenge to organizations, enterprises and governments at all levels, and will undoubtedly influence the way people work and live in future decades. Accelerated depletion of natural resources and pollution caused by the increased use of technical products are key contributors to climate change [1]. Improved recognition of this has led increased political pressure to impose more stringent regulations on both the manufacturers and the end users of such products. In 2000, carbon dioxide equivalent (CO_2e) emissions represented about 65% of global green house gas emissions, as opposed to about 24% and 14% respectively produced by power generation and industrial activity [2]. A recent survey conducted by the U.S. Energy Information Administration found that, in 2013, the global industrial sector consumed about one-half of the world's total energy production, emphasizing the importance of effective energy management in the industrial sector. Manufacturing is the key industrial sector, and a large and growing number of manufacturers are realizing substantial financial and environmental benefits from instituting sustainable business practices. Sustainable manufacturing, defined as making products through economically-sound processes that minimize negative environmental impacts through the conservation of energy and natural resources, has then become an increasingly important focus of attention both in industry and academia.

A key approach for achieving sustainable manufacturing is to reduce carbon emissions by reducing energy usage, and this trend has recently been extended to machining technologies and operations [1,3,4]. A significant amount of research has been devoted to environmental issues related to machine tool system usage. Most of these studies focus on electricity consumption related to chipping processes, material removal and cutting fluids (Santo et al., 2011). However, a machining tools rely on electricity, and Santos et al. [5] noted that modern machine tool systems are a key industrial energy consumer, with most power being used to drive spindle rotation and servo-driven axis movement [4]. Optimizing cutting parameters is imperative to minimizing energy consumption during machining. Optimization of machining conditions has been studied for decades, but most such studies were based on machining science and economic considerations without accounting for the environmental dimension. Mativenga and Rajemi [6] concluded that minimizing energy consumption can significantly reduce the cost, energy and carbon footprint of machined products.

From the macro-level perspective, a manufacturing system consists of several modern CNC machine tools, and traditional

* Corresponding author. Fax: +886 4 24510240.

http://dx.doi.org/10.1016/j.rcim.2015.10.010
0736-5845/

Table 1
Detailed descriptions for jobs.

Job	Material	Specific energy(Nm/mm^3)	Originaldiameter (mm)	Length (mm)	Final diameter (mm)	Depth of cut (mm)	Feed (mm/rev)	Cutting conditions Spindle (RPM)			
								1	2	3	4
1	Carbon steel	1.6	80	450	50	15	0.25	550	417	350	250
2			250	710	240	5		409	330	257	200
3			400	210	380	10		200	150	143	110
4	Alloy steels	4.4	211	148	197	7		144	105	88	79
5			253	230	512	11.5		80	71	55	39
6			336	204	325.2	5.4		100	85	77	50
7			259	622	246.1	6.45		300	270	255	225
8	Cast irons	1.1	76.3	332.5	57.5	9.4		1350	1190	1000	850
9			359	123	308.2	25.4		77	60	50	40
10			176.5	58	147.3	14.6		318	273	199	165
11			213.4	157.6	196	8.7		553	429	355	303
12	Stainless steel	2.8	142.2	632	121.8	10.2		355	273	245	192
13			269.3	381	242.9	13.2		89	71	58	50
14			156.8	226	137.8	9.5		230	204	163	133
15			337.5	151.6	313.1	12.2		155	142	100	73
16	Magnesium	1.1	99.3	155	58.7	20.3		444	394	300	228
17	alloys		108	206	94.3	6.85		1000	893	749	664
18			65	445	30.4	17.3		800	749	691	599
19	Bronze	2.2	273.8	326.5	244.2	14.8		150	123	90	77
20	Aluminum	0.7	346.9	68.7	299.3	23.8		173	145	109	127

sequencing and scheduling models are used to account for economic issues such as costs, makespan, job tardiness, throughput, etc. However, tools for solving production scheduling problems largely ignore energy saving considerations. In this paper we consider a problem involving the scheduling of a set of jobs on parallel machines with different machining conditions for each job. The system objective is to minimize makespan given a maximum threshold for power consumption during machining. The remainder of this paper is organized as follows. Section 2 reviews parallel machine scheduling problems with flexible resources. Section 3 introduces the considered problem in detail. Section 4 proposes a two-stage heuristic for solving the illustrated problem. Section 5 reports the computation result of each stage of the proposed heuristic. Section 6 presents conclusions and suggestions for further research.

2. Literature review

Most studies for classical parallel machine scheduling problems assume that jobs have fixed processing times. However, in reality, processing times fluctuate with the amount of resources allocated, including manpower, financial support, fuel, energy, etc. Shabtay and Steiner [7]. Nowicki and Zdralka [8] examined controllable processing times in single or two-machine scheduling problems, while Shabtay and Steiner [7] provided a more comprehensive survey of results for scheduling problems with controllable processing times, reviewing previous studies for both single and multi-machine problems. Edis et al. [9] classified prior studies in a framework based on five categories: machine environment, additional resources, objective functions, complexity results, and solution methods.

Daniels and Mazzola [10] noted that resource flexibility in a flow shop environment can have a significant impact on schedule quality when job processing times depend on the amount and mix of resources dedicated. Daniels et al. [11] further demonstrated that improvements to operational performance can be achieved through the deployment of flexible resources in an environment of parallel manufacturing cells. They provided mathematical formulations for two versions (static and dynamic) of the Parallel-Machine Flexible-Resource Scheduling problems (PMFRS). In static PMFRS problems, resource allocation decisions remain unchanged throughout the scheduling horizon. In dynamic PMFRS problems, resources can be reassigned to machines at any time once a job is completed. If the jobs are not assigned to specific machines, the problem is called an unspecified PMFRS (UPMFRS) problem, requiring the solution of an additional job-machine assignment subproblem. Daniels et al. [12] proposed and compared two heuristics for testing over 800 static UPMFRS. They concluded that the tabu search-based heuristic outperformed the decomposition heuristic in terms of cost and effectiveness for determining an optimal solution. Edis and Oguz [13] extended the formulation of dynamic PMRFS problems proposed by Daniels et al. [11] and presented mathematical models for static and dynamic UPMFRS problems. The static PMFRS problem can be solved in polynomial time, while the dynamic PMFRS, and the static and dynamic UPMFRS problems are all NP-hard [11,12].

3. Problem statement

The UPMFRS problem considered in this study may be stated as follows: 20 independent single-operation jobs are available for processing at time $t=0$. For each job, the manufacturer engineers and cutting tool providers suggest four potential cutting conditions (processing modes). The detailed job descriptions for all the 20 jobs are presented in Table 1. All the options and their corresponding machining times and power demands are listed in Table 2. Each job can be processed on any of 3 identical CNC turning machines. Each machine can process at most one job at a time, and job preemption is not allowed in this case. The objective is to minimize the makespan for all 20 jobs.

The only constraint is that at any time the electrical power demand peak cannot exceed 25 KW for job production with the 3-machine cell. The upper bound of the power demand can be viewed as an additional flexible resource as it is continuous and renewable, whereas the number of machines is fixed. When the cutting condition for a turning operation is determined, we can calculate the material removal rate (MRR) defined as the volume of material removed per unit time. Given the specific cutting energy of the workpiece material, the power demand for a given cutting parameter setting can be obtained by multiplying the specific

Please cite this article as: Y.-C. Wang, et al., Selection of cutting conditions for power constrained parallel machine scheduling, Robotics and Computer Integrated Manufacturing (2015), http://dx.doi.org/10.1016/j.rcim.2015.10.010