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A multi-objective teaching–learning-based optimization algorithm to scheduling in turning processes for minimizing makespan and carbon footprint

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A B S T R A C T

Industry is responsible for nearly half of the global energy consumption. Recent studies on sustainable manufacturing focused on energy saving to reduce the unit production cost and environmental impacts. Besides energy consumption, certain manufacturing activities in machine shops, such as the use of cutting fluids, disposal of worn tools, and material consumption, also cause other environmental impacts. Since all these activities lead to carbon footprint directly or indirectly, carbon footprint can be employed as a new and overall environment criterion in manufacturing. In this study, an integrated model for processing parameter optimization and flow-shop scheduling was developed. Objectives to minimize both makespan and carbon footprint were considered simultaneously, which was solved by a multi-objective teaching–learning-based optimization algorithm. Furthermore, three carbon-footprint-reduction strategies were employed to optimize the scheduling results: (i) postponing strategy, (ii) setup strategy, and (iii) processing parameter preliminary optimization strategy. In the theoretical aspect, the strategies greatly improved the performance of the optimization results through reducing machine idle time and cutting down the search space. From the perspective of practical applications, these strategies greatly help elevate production efficiency and reduce environmental impacts.

1. Introduction

According to the International Energy Outlook 2013 (EIA, 2013b), global energy consumption was 524 quadrillion British thermal units (Btu) in 2010, and is expected to rise to 630 quadrillion Btu in 2020 and to 820 quadrillion Btu in 2040. Energy consumption has a negative impact on the environment. Use of fossil fuels generates direct emission of greenhouse gases, for example, carbon dioxide (CO_2). Although the consumption of electricity does not generate CO_2 directly, CO_2 is released into the environment during power generation. The average emission factor for electricity was 0.5488 kg per kWh in China in 2009 (NDRC, 2011), indicating that 0.5488 kg CO_2 was produced when 1 kWh electricity was generated. In 2008, the total CO_2 emission of the USA was ~5802 million metric tons, and 27.4% of that was contributed by industry (EIA, 2009). The significant increase in CO_2 level has caused greenhouse effect and resulted in global warming (IPCC, 2006). Furthermore, the concern over energy consumption is heightened by the rapid increase in the price of fossil fuels and electricity. The price of West Texas Intermediate fuel was 81.08 U S. dollars per barrel in 2011, which is expected to rise to 115.36 U S. dollar per barrel in 2025 and 160.68 U S. dollar per barrel in 2040 (EIA, 2013a). Regarding industry, the unit production cost of products will increase because of the rapid increase in the energy price. Thus, manufacturers are eager to reduce energy consumption considering all the relevant social, economic, and environmental issues.

In industry, energy is primarily consumed by production equipment during production, which is basically the machine tool

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Nomenclature

$a_{sp,j}$	the cutting depth of job j, $j = 1, 2, \ldots, n$;
C_{ik}	the completion time of the kth job in a specific schedule on a machine i; $i = 1, 2, \ldots, m$; $k = 1, 2, \ldots, n$;
$C_{\max}$	the maximum completion time or makespan, which is equal to the completion time of the last job processed in machine m;
$CE_{p,ij}$	the carbon footprint during the processing of job j on machine i, which can be obtained by using Eq.(16), $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$;
$d_{w,j}$	the diameter of job j, $j = 1, 2, \ldots, n$;
f_{ij}	the feed rate of job j on machine i, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$;
E_{ik}	the departure time of operation O_{ik}, $i = 1, 2, \ldots, m$; $k = 1, 2, \ldots, n$;
$F_{c,ij}$	the cutting force for job j on machine i, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$; $F_{c,ij}$ can be calculated by using Eq.(9);
h_j	the margin of job j, $j = 1, 2, \ldots, n$;
I_{ik}	the idle time between the processing of the kth job and k+1th job in the schedule on machine i, $i = 1, 2, \ldots, m$; $k = 1, , 2, \ldots, n$;
k	the kth job in a specific schedule $j_1, j_2, \ldots, j_k, \ldots, j_n$; $k = 1, 2, \ldots, n$;
$l_{w,j}$	the length of job j plus length of the leads, $j = 1, 2, \ldots, n$;
m	the number of machines;
n	the number of jobs;
$n_{w,ij}$	the spindle revolution of job j on machine i, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$;
p_{ij}	the processing time for job j on machine i, equals to the sum of $t_{m,ij}$ and $t_{t,i}$, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$;
$P_{u0,\ i}$	the minimum idle power of machine i, $i = 1, 2, \ldots, m$;
$t_{m,ij}$	the cutting time of job j on machine i, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$; $t_{m,\ ij}$ can be calculated by using Eq. (17);
$t_{t,i}$	the preparationtime needed before one jobis processed at machine i, $i = 1, 2, \ldots, m$;
$V_{c,ij}$	the cutting velocity for job j on machine i, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$;$V_{c,ij}$ can be calculated by using Eq. (14);

and the cost of electricity consumed by machine tools over a decade is ~100 times higher than their purchase cost (Camposeco-Negrete, 2013). Electricity, cutting fluid, wear and tear of cutting tools, material consumption, and disposal of chips were all found to cause carbon footprint in a machining system (Li et al., 2013). The carbon footprint model introduced by Li et al. (2013) analysed the economic and environmental effects on manufacturing in addition to electricity.

Several studies emphasized on sustainable manufacturing in a discrete manufacturing system. However, most of them focused on energy saving. In the processing parameter optimization domain, design of experimental methodologies has been applied to investigate the effects of processing parameters on the energy-related response variables. The effects of metal-cutting parameters on the surface roughness and power consumption have been investigated by employing orthogonal array, signal-to-noise (S/N) ratio, and analysis of variance (ANOVA) (Fratila and Caizar, 2011). The specific process energy and surface roughness were modelled as a function of metal-cutting parameters (Guo et al., 2012). They proposed a two-step procedure: (i) identification of the metal-cutting process region where a specified surface roughness occurred; (ii) determination of the optimal metal-cutting parameters for guaranteeing the minimum energy consumption. Yan and Li (2013) reported a multi-objective optimization method with three objectives, including surface roughness, material removal rate, and cutting energy. They applied the weighted grey relational analysis technique and response surface methodology and the results showed that the most significant parameter was the width of cut.

In the field of energy modelling, most of energy predicting methodologies and models proposed are off-line. Avram and Xirouchakis (2011) proposed an effective methodology to calculate the total energy consumption of a machine. Mori et al. (2011) pointed out that the power consumption of machines could be classified as basic power, idle power, and cutting power, and could be conceived as constant power consumption with specific cutting conditions. He et al. (2012) investigated the power characteristic of each energy-consuming component of machines. The energy model developed by He et al. (2012) was proved to be complex and limited when compared to Gutowski et al. (2006) and Kara and Li (2011)'s studies (Balogun and Mativenga, 2013). Balogun and Mativenga (2013) developed a new mathematical model for predicting the energy consumption during the entire machine operation period. However, Hu et al. (2012) proposed an on-line energy predicting approach which could estimate the variable energy consumption of the machines according to the power balance equation and additional load loss function.

In scheduling optimization domain, a single-machine scheduling mathematical model has been proposed for the minimization of total energy consumption and total tardiness, which was solved by a novel greedy heuristic search method (Mouzon and Yildirim, 2008). They solved this model using a modified multi-objective genetic algorithm. Both production efficiency and time-of-use electricity cost were considered in the hybrid flow-shop scheduling problem (Luo et al., 2013). The proposed ant colony optimization algorithm has been proved to be more effective and efficient than non-dominated sorting genetic algorithm and strength Pareto evolutionary algorithm 2. They also proved that a longer off-peak period and the use of faster machines can reduce the electric power cost and makespan. A genetic algorithm-based scheduling method was introduced to solve the flexible job-shop dynamic scheduling problem, where the minimum or maximum energy consumption was considered (Zhang et al., 2013). In classical job-shop problem, minimum total energy consumption and total weighted tardiness were treated as two objectives (Liu et al., 2013). An energy efficient-aware flexible flow-shop scheduling model was developed, which is solved through an improved genetic-simulated annealing algorithm; an apparently conflicting relationship between makespan and energy consumption was observed (Dai et al., 2013).

One aim of this study is to investigate the scheduling problem using carbon footprint and makespan. A carbon footprint-aware job-shop scheduling model was established to minimize carbon footprint and makespan simultaneously by Yi et al. (2012). A ε-archived genetic algorithm was developed to solve the batch scheduling problems with two goals, i.e., to minimize carbon footprint and total weighted tardiness by Liu (2013). In his study, carbon footprint was only caused by electricity consumption. However, carbon footprint can also be caused by cutting fluid, wear and tear of cutting tools, material consumption, and disposal of chips in a machining system (Li et al., 2013). Neither of the studies considered the optimization of the processing parameters of machining operations. Fang et al. (2011) proposed a goal programming model in which the sequencing of jobs and cutting velocities of machine tools acted as decision variables. However, the accuracy of their calculation methods for power and energy consumptions is hardly satisfying, and the goal programming method cannot be applied for large-size problems.