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Optimising the machining time, deviation and energy consumption through a multi-objective feature sequencing approach

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ABSTRACT

A considerable amount of global energy consumption is attributable to the machining energy consumption of the machine tool. Thus, reducing the machining energy consumption can alleviate the energy crisis and energy-related environmental pollution. It has been approved that feature sequencing is an effective and economical approach to reduce the machining energy consumption. The single objective model that only minimises the machining energy consumption has been developed in previous research. However, the machining time and deviation, which are also affected by the feature sequence, have not been considered. Thus, this article first aims to understand and model the sequence-related machining time, deviation, and energy consumption (S-MT, S-MD, and S-MEC) while machining a part. Accordingly, a multi-objective feature sequencing problem, which optimises the trade-off among S-MT, S-MD, and S-MEC, is introduced. To solve it, two optimisation approaches, including Non-dominated Inserting Enumeration Algorithm (NIEA) and Non-dominated Sorting Genetic Algorithm II (NSGA-II), are proposed and employed. A case study was conducted to demonstrate the developed models and the optimisation approaches. The experiment results show that the optimal or near-optimal solution sets can be obtained for eight machine parts. By comparison, 20.51% S-MT, 5.29% S-MD, and 16.66% S-MEC can be reduced. Between the two algorithms, NIEA is recommended for the part that has fewer than 12 features. Finally, more optimisation approaches for the multi-objective problem are proposed and discussed.

1. Introduction

Increasing energy price and requirements to improve energy efficiency are the new challenges faced by modern manufacturing enterprises [1]. Machine tools are widely used in manufacturing sector [2] and consume considerable amounts of energy [3]. For instance, there are over 7 million machine tools in China, whose total power can achieve 70 million kilowatts [4]. Moreover, surveys showed that the energy efficiency of machine tools is generally less than 30% [4]. Thus, reducing the energy consumption of machine tools has been identified as a potential approach to improving manufacturing energy efficiency [5], and it has attracted attention from both academic research and industrial applications [6].

Energy-aware process planning and scheduling are two effective management approaches to reduce the energy consumption of machine tools [7]. Adequate research on energy-aware scheduling in manufacturing has been conducted [8] and achieved the target for reducing the idle energy consumption [9]. On the other hand, research on energy-aware process planning has been focused on process parameters optimisation [10] and achieved the target for reducing the machining energy consumption [11]. For example, a recent work by Shin [12] presented the novel component modelling and online optimisation of cutting parameters (feed rate, spindle speed, cutting depth and width) to minimise the milling machining energy consumption in real-time. However, energy-aware feature (operation) sequencing research is still insufficient, which restricts the energy-aware process planning.

The energy-aware feature sequencing aims at determining the processing sequence of features of a part (PSFP) that minimises the

Abbreviations: BTT, bottom-to-top; CNC, computer numerical control; GNEA, genetic-based non-dominated enumeration algorithm; MOEAs, multi-objective evolutionary algorithms; MOPs, multi-objective problems; NIEA, non-dominated inserting enumeration algorithm; NSGA-II, non-dominated sorting genetic algorithm II; PSFP, processing sequence of features of a part; PSFPs, processing sequences of features of a part; rpm, revolutions per minute; SI, supplementary information; S-MD, sequence-related machining deviation [μm]; S-MEC, sequence-related machining energy consumption [J]; S-MP, sequence-related machining process; S-MT, sequence-related machining time [s]; S-ND, sequence-related non-cutting deviation [μm]; S-NEC, sequence-related non-cutting energy consumption [J]; S-NT, sequence-related non-cutting time [s]

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Nomenclature

α_A angular acceleration of the spindle [rad/s^2]
B monomial coefficient in the S-ND model for the feeding activity
$d_j^{(F_p,F_q)}$ S-ND for the j-th feeding activity from the feature F_p to the feature F_q [μm]
D_s total S-MD based on a specific PSFP [μm]
$D_{cut}^{S_k}$ sequence-related cutting deviation for the feature at the k-th position of the sequence [μm]
$D_{non}^{(S_k,S_{k+1})}$ S-ND between the features at the k-th and $k+1$-th positions of the sequence [μm]
$E_{cut}^{S_k}$ sequence-related cutting energy consumption for the feature at the k-th position of the sequence
$E_{non}^{(S_k,S_{k+1})}$ S-NEC between the features at the k-th and $k+1$-th positions of the sequence [J]
E_s total S-MEC based on a specific PSFP [J]
F a finite set of $n+2$ features of a part in machining environment, $F=\{F_i\}_{i=0}^{n+1}$, $F_C\subset F$
F_0, F_{n+1} virtual features to denote the start and end positions of the tool while machining a part
F_C a finite set of n actual features of a part, $F_C=\{F_i\}_{i=1}^{n}$
F_i i-th feature in a part
F_p, F_q specific features in a part
g index for the speed change of the spindle rotation
i index for the feature in a part
j index for the feeding activity in a tool path
k index for the position in a feature sequence
l_j^{pq} sequence-related non-cutting distance for the j-th feeding activity between the features F_p and F_q [mm]
m number of feeding activities in a tool path between two features
n number of actual features in a part
n_{Sg}^{pq}, n_{Eg}^{pq} initial and end speed of the g-th speed change of the spindle rotation in the non-cutting from the feature F_p to the feature F_q [rpm]
N population size in NSGA-II
P_t parent population that is created at the $(t+1)$-th generation
Q_t offspring population that is created at the $(t+1)$-th generation
R_t population that is created by the combination of P_t and Q_t at the $(t+2)$-th generation
S a finite set to indicate all of the positions of the features in a sequence, $S=\{S_k\}_{k=1}^{n+2}$
S_k feature at the k-th position of a sequence
t index for the generation in NSGA-II
$t_{pj}^{(F_p,F_q)}$ time for the j-th feeding activity in the non-cutting from the feature F_p to the feature F_q [s]
$t_{sg}^{(F_p,F_q)}$ time for the g-th speed change of the spindle rotation in the non-cutting from the feature F_p to the feature F_q [s]
$T_{cut}^{S_k}$ sequence-related cutting time for the feature at the k-th position of the sequence [s]
$T_{non}^{(S_k,S_{k+1})}$ S-NT between the features at the k-th and $k+1$-th positions of the sequence [s]
T_s total S-MT based on a specific PSFP [s]
$T_{src}^{(F_p,F_q)}$ S-NT for the spindle speed change in the non-cutting from the feature F_p to the feature F_q [s]
$T_{tc}^{(F_p,F_q)}$ S-NT for the tool change in the non-cutting from the feature F_p to the feature F_q [s]
$T_{tp}^{(F_p,F_q)}$ S-NT for the tool path in the non-cutting from the feature F_p to the feature F_q [s]
u index for the solution in NIEA
w number of speed changes of the spindle rotation between two features
z natural number
ΔX_j^{pq}, ΔY_j^{pq}, ΔZ_j^{pq} sequence-related relative distances of X-axis, Y-axis, and Z-axis between the start and end coordinate positions in the j-th feeding activity from the feature F_p to the feature F_q [mm]

machining energy consumption of a machine tool. In existing studies, the single objective is a limitation [13]. In real manufacturing circumstance, it is not reasonable to only reduce the machining energy consumption without controlling the machining time and deviation, which can cause the problems of machine tool tardiness and product quality. In related research, Shin [12] suggested that the machining time could be considered as another objective in addition to the machining energy consumption in the formulation of an optimisation problem. However, there was an opinion that the machining time was positively correlated with the machining energy consumption [14]. As a result, the minimisation of the machining energy consumption could always result in the minimum machining time. If this opinion was true, it would be redundant to develop the machining time model. It is important to investigate this opinion. Yan [15] and Kant [16] verified the conflict between the machining quality (deviation) and energy consumption, and the machining deviation model should be developed. The lack of identification and extraction of the sequence-related machining process (S-MP) is another limitation. The S-MP is defined as the process that is affected by the PSFP. The machining time, deviation, and energy consumption for completing the S-MP are called the sequence-related machining time, deviation, and energy consumption (S-MT, S-MD, and S-MEC). Bridging the gaps and insufficiencies to model and solve the multi-objective problem has motivated this research, and the proposed solutions are the main contributions of this paper.

In our study, it is assumed that all of the required processing for a part can be finished on a single machine tool. If a part requires more than one machine tool, the features to be processed on the same machine can be sorted and separately sequenced. Besides, each feature does not have the volumetric intersection with other features. Our study aims at analysing the conflict between the S-MT and the S-MEC when processing a part, and at integrating the S-MT and S-MD models with the existing S-MEC model to obtain the multi-objective model. This article investigates a novel management approach to reduce the S-MT, S-MD, and S-MEC by merely adjusting the PSFP. The multi-objective optimisation in this research is to achieve the optimal trade-offs among the aforementioned three objectives. A deterministic method, Non-dominated Inserting Enumeration Algorithm (NIEA), and a popular evolutionary algorithm, Non-dominated Sorting Genetic Algorithm II (NSGA-II), are proposed and used as the optimisation approaches to search for the non-dominated set of optimal solutions. Furthermore, a novel hybrid algorithm named Genetic-based Non-dominated Enumeration Algorithm (GNEA) is proposed and compared. An optimal solution represents a PSFP that results in the optimal trade-off among the three objectives. Based on case studies, the developed models and optimisation approaches are demonstrated, compared, and discussed.

In the remainder of this paper, the literature review is presented in the next section. The problem description and the multi-objective model are given in Section 3. In Section 4, the working procedures of NIEA and NSGA-II for optimising the three objectives are described. A case study is conducted to demonstrate the multi-objective feature sequencing approach in Section 5. In Section 6, more optimisation approaches for the feature sequencing problem are analysed and discussed. Finally, a brief summary and a description of future work are given in Section 7.