Energy 121 (2017) 292–305

Contents lists available at ScienceDirect

Energy

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

Minimising the machining energy consumption of a machine tool by sequencing the features of a part

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ARTICLE INFO

Article history:
Received 27 August 2016
Received in revised form
5 December 2016
Accepted 7 January 2017
Available online 11 January 2017

Keywords:
Machining energy
Machine tools
Feature sequencing
Cutting volume
Depth-First Search
Genetic Algorithm

ABSTRACT

Increasing energy price and emission reduction requirements are new challenges faced by modern manufacturers. A considerable amount of their energy consumption is attributed to the machining energy consumption of machine tools (MTE), including cutting and non-cutting energy consumption (CE and NCE). The value of MTE is affected by the processing sequence of the features within a specific part because both the cutting and non-cutting plans vary based on different feature sequences. This article aims to understand and characterise the MTE while machining a part. A CE model is developed to bridge the knowledge gap, and two sub-models for specific energy consumption and actual cutting volume are developed. Then, a single objective optimisation problem, minimising the MTE, is introduced. Two optimisation approaches, Depth-First Search (DFS) and Genetic Algorithm (GA), are employed to generate the optimal processing sequence. A case study is conducted, where five parts with 11–15 features are processed on a machining centre. By comparing the experiment results of the two algorithms, GA is recommended for the MTE model. The accuracy of our model achieved 96.25%. 14.13% and 14.00% MTE can be saved using DFS and GA, respectively. Moreover, the case study demonstrated a 20.69% machining time reduction.

1. Introduction

An enormous amount of energy (549 quadrillion Btu in 2012) is consumed annually worldwide with an estimated increase of 1.4% per year, and the global energy-related carbon dioxide (CO_2) emissions are expected to rise from 32 billion metric tons in 2012 to 36 billion metric tons in 2020 [1]. A large proportion (approximately 25%) is attributable to manufacturing [2,3], and reducing the manufacturing energy consumption and CO_2 emissions becomes significant for alleviating the energy crisis and environmental pollution [4–6]. Machine tools are the basic devices in manufacturing that consume considerable amounts of energy [3,7,8]. According to statistics from the U.S energy information administration, the electricity consumption of machine tools has accounted for above 50% of the total manufacturing electricity consumption [3,9]. Thus, reducing the energy consumption of machine tools has attracted a large amount of attention from both academic research and industrial applications [10,11].

The first step toward reducing the energy consumption of machine tools is to understand and characterise their energy consumption [12]. In particular, a considerable amount of energy that is consumed by machine tools is attributable to the energy consumption of a machine tool by completing a feasible processing plan for a specific part (MTE) [8], and the MTE can be divided to two types: the cutting and non-cutting energy consumption (CE and NCE) [4,13]. The NCE is defined as the energy consumption during run-time operations, including the tool path, tool change and change of spindle rotation speed [14]. The energy consumed when

Abbreviation: ACV, actual cutting volume [cm^3]; BTT, bottom-to-top; CE, cutting energy consumption of the machine tool [J]; DFS, Depth-First Search; GA, Genetic Algorithm; IEP, inclusion-exclusion principle; MTE, machining energy consumption of the machine tool [J]; NCE, non-cutting energy consumption of the machine tool [J]; SEC, specific energy consumption [J/cm^3]; SI, supplementary information.

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http://dx.doi.org/10.1016/j.energy.2017.01.039

Nomenclature

Feature sequencing problem

- i, k indices for the features in a part and the positions in a feature sequence
- n number of the actual features in a part
- F_i i-th feature in a part
- F_C a finite set of n features of a part, $F_C = \{F_i\}_{i=1}^{n}$
- F a finite set of $n+2$ features of a part in a machining environment, $F = \{F_i\}_{i=0}^{n+1}$, $F_C \subset F$
- F_p a specific feature in a part
- F_0, F_{n+1} virtual features to denote the start position and end position of a tool while machining
- W width of a groove
- w, h diameter and depth of a hole
- H depth of a hole with its interactive volume included
- S_k feature at the k-th position of a sequence
- S a finite set to indicate all of the positions of the features in a sequence, $S = \{S_k\}_{k=1}^{n+2}$

Energy consumption

- E_s total MTE based on a specific feature sequence [J]
- $E_{non}^{(S_k,S_{k+1})}$ NCE between the feature at the k-th position and the feature at the $k+1$-th position of the sequence [J]
- $E_{cut}^{F_i}$ CE for the feature F_i [J]
- $E_{cut}^{S_k}$ CE for the feature at the k-th position [J]
- SEC_i specific energy consumption for the feature F_i [J/cm^3]
- v_i actual cutting volume for the feature F_i [cm^3]
- P_i cutting power of the machine tool for the feature F_i [W]
- MRR_i material removal rate for the feature F_i [cm^3/s]
- a_i, e_i, f_i milling depth [mm], milling width [mm], feed rate [mm/tooth], tooth
- N_i, r_i number and spindle rotation speed [rpm], respectively, for the feature F_i
- D_i drilling diameter for the feature F_i. [mm]
- P_{MCi}, P_{AFi}, P_{SRi} material removal power, axial feeding power and spindle rotation power of the machine tool, respectively, for the feature F_i [W]
- C_M coefficient in the material milling power model
- v_{si} cutting speed for the feature F_i [m/min]
- w_M, y_M, x_M, u_M exponent of cutting speed, feed rate, milling depth and milling width, respectively, in the material milling power model
- C_D coefficient in the material drilling power model
- z_D, y_D exponent of drilling diameter and feed rate, respectively, in the material drilling power model
- P_{XFi}, P_{YFi}, P_{ZFi} feeding power of the X-axis, Y-axis and Z-axis, respectively, while cutting the feature F_i [W]
- v_{fi} feeding speed for the feature F_i [mm/min]
- α_i angle between the feeding direction of the tool and the X-axis while cutting the feature F_i
- V_i cutting volume for the feature F_i with its interactive volume included [cm^3]
- G_j cutting volume for the feature at the j-th position with its interactive volume included [cm^3]
- $j_1, j_2, j_{(M-1)}$ indices for the specific positions in a feature sequence
- M maximum number of the features that interact with one another simultaneously in the part

Machining time

- T_s total machining time based on a specific feature sequence [s]
- $T_{non}^{(S_k,S_{k+1})}$ non-cutting time between the feature at the k-th position and the feature at the $k+1$-th position of the sequence [s]
- $T_{cut}^{S_k}$ cutting time for the feature at the k-th position of the sequence [s]

Machine tool related parameters

- P_{CS}, P_0 coolant spray power and standby power of the machine tool [W]
- A_{XF}, A_{YF}, A_{ZF}^{U}, A_{ZF}^{D} quadratic coefficient in the feeding power model of X-axis, Y-axis, Z-axis upward and Z-axis downward, respectively
- B_{XF}, B_{YF}, B_{ZF}^{U}, B_{ZF}^{D} monomial coefficient in the feeding power model of X-axis, Y-axis, Z-axis upward and Z-axis downward, respectively
- $B_{SR}^{r_i}$, $C_{SR}^{r_i}$ monomial coefficient and constant in the spindle rotation power model at the rotation speed of r_i

Algorithms

- N number of the chromosomes at an iteration

a part is actually cut by a machine tool can be defined as the CE [15]. It has been proved that the values of both CE and NCE are affected by the feature processing sequence of a part [8,14,15]. Finding the sequence that results in the smaller value of the NCE has been proved to be an effective energy consumption reduction approach, and modelling work for the NCE has been developed by Hu [14]. However, the potential for this approach to reduce the CE has not been well explored, and the understanding of the CE is not sufficient in existing research. Usually, the CE accounts for above 60% of the total MTE [8,16].

The CE can be modelled by multiplying the specific energy consumption (SEC) with the actual cutting volume (ACV) [15,17]. The feature processing sequence of a part can affect the value of the CE, because the ACV for a feature can vary if any of its preceding features on the processing sequence are replaced by another feature, while the SEC for the features is different [18,19]. In the existing modelling work for the CE, there are some insufficiencies. For example, the energy of the machine tool is consumed for the axial feeding, spindle rotation, coolant spray, and additional load losses while cutting the features, but these energy portions have not been added to the SEC model, which harm the model's accuracy. Moreover, the mathematic relationship between the processing sequence and the ACV of each feature has not been developed in the CE model, and it is a challenging work to dynamically reflect the relationship. Bridging important gaps and insufficiencies to model and optimise the CE within the MTE has motivated this research, and the proposed solutions are the main contributions of this paper.

Based on the above, this study aims at understanding and characterising the CE and at integrating the developed CE model with the existing NCE model to obtain the completed MTE model. To improve the accuracy, two sub-models have been developed to