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A hybrid process planning for energy-efficient machining: Application of predictive analytics

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Abstract. Computer-aided process planning for energy-efficient machining is essential as energy consumption becomes a major environmental metric in the metal cutting industry. This paper introduces a process planning approach that enables energy prediction in the process planning phase through incorporating Generative Process Planning (GPP) and Variant Process Planning (VPP), called Hybrid Process Planning. GPP is used to provide decision making algorithms in computers by generating energy prediction models specific for machining conditions. VPP is adopted to reuse existing process plans with inclusion of such prediction models so that process planners can anticipate the energy values to be consumed in machine tools. Particularly, the present approach builds upon predictive analytics to efficiently handle sensor-level data collected from real machining operations, and create energy prediction models by using a machine-learning technique.

1. Introduction

In metal cutting processes, process planning is mandatory to determine individual machining operations and strategies needed to fabricate a part [1]. Due to the multi-functionality of machine tools and the complexity of process planning, Computer-Aided Process Planning (CAPP), which uses computers for process planning, becomes essential to gain better speed, cost and time [1]. Recently, environmentally conscious (eco-) manufacturing receives much attention to enhance environmental performance [2] and energy consumption particularly becomes an important environmental metric [3]. Thus, eco-CAPP systems considering the energy aspect are vital for realizing energy-efficient machining.

However, few studies have been made for providing eco-CAPP systems. The previous studies including [3] [4] [5] and [6] have contributed to embody energy-efficient machining through providing logical procedures in the domain of CAPP. The methods introduced in those studies are mainly based on Generative Process Planning (GPP). As GPP uses the algorithms implemented in computers to create process plans automatically without human intervention [7], it requires algorithm coding to decide their process parameters using energy prediction models. However, GPP has not been much propagated to industries because it serves the algorithms restricted under limited experimental conditions [8]. Unless such algorithms dynamically calibrate their models into changes in machining conditions, they lack in providing predictive results accurately for a huge number of machining conditions.

Meanwhile, Variant Process Planning (VPP) is based on Group Technology (GT), which identifies part families and their standard plans with regard to their classification attributes [7]. If an



inputted part can be classified with a code number and its relevant standard plan exists in a standard process plan database, this standard plan would be retrieved through similarity search. If a part doesn't have relevant standard plans, the most-similar plan would be retrieved. Due to this simplicity, VPP is more usable in industries; however, it also has a drawback [8]. VPP hardly provides predictive algorithms for improving performance because it only reuses existing standard plans.

This paper introduces a CAPP approach for energy-efficient machining based on Hybrid Process Planning (HPP), which integrates advantages of GPP and VPP. This paper also contains a case study to demonstrate the feasibility of the proposed approach. The proposed approach: 1) uses sensor-level machine-monitoring data collected from previous machining executions for creating energy models, 2) applies GPP to create machine-specific energy models that can predict energy up to the level of tool paths, and 3) advances traditional VPP to enable model-based process planning through providing standard process plans together with such energy models. Therefore, the proposed approach makes CAPP systems feasible so that process planners proactively forecast energy consumption during process planning. The present work is an attempt of predictive analytics in that it aims at implementing a data-driven prediction environment to learn the past knowledge from sensor-level data.

Section 2 introduces the concept of the proposed approach. Sections 3 and 4, respectively, explain the methods of energy predictive modelling and model-based process planning. Section 5 shows a case study, and Section 6 concludes the remark. Note that the concept of HPP has been introduced like [8]. It is also noted that STEP-compliant data interface for Numerical Controller (STEP-NC) [9] is chosen as the data interface for process planning and MTConnect [10] as the data interface for machine-monitoring.

2. Proposed approach

Figure 1 shows the concept of the proposed approach. It comprises the two stages: preparatory and operation (these are the generic stages in VPP). The preparatory stage pre-identifies standard process plans with generating energy models before their use in the operation stage. This stage adopts the concept of GPP. On the other hand, as the operation stage builds upon the traditional VPP, it retrieves and edits standard plans with the use of energy models during the process planning phase. Here, an energy model is defined as a numerical function that characterizes the relationship between x variables (process parameters: feedrate, spindle speed, cutting depth and cutting width) and y variable (energy) at a certain set of Machining Configuration (MC) parameters. An energy model provides the ability to predict energy at the level of tool paths. The MC parameters are the classifier for identifying a specific machining condition where an energy model can be applied. Note that the machining data consist of process plan, Numerical Control (NC) program and machine-monitoring data.

3. Methods for preparatory stage

Section 3 explains technical methods for individual functions in the preparatory stage, which consist of data elements identification, data synchronization, prediction modelling, and model accumulation.

3.1. Data elements identification

This function defines the data elements that should be extracted from machining data to acquire the data instances for energy modelling. Specifically, this function identifies the data elements regarding x variables, y variable and a set of MC parameters while the data elements can be designated among process plan, NC program and machine-monitoring data. We first define a list of MC parameters (M) as below. Here, *command* stands for an NC block code such as G00 or G01, and *trajectory* does the specific purpose of an NC block code.

$$M = \{ m_1, m_2, m_3, m_4, m_5, m_6, m_7 \mid \text{machine, material, operation, feature, strategy, command, trajectory} \}$$

Then, we define x variables as the four process parameters - feedrate (x_1), spindle speed (x_2), cutting depth (x_3) and cutting width (x_4) - and y variable as delta energy as below. Here, we use the concept of delta energy, which multiplies power with a sampling time interval of measuring power [11]. It comes

from that a power meter typically measures not energy directly but power at each timestamp because energy-unit is a scalar quantity [12].

$$(X, y)_M = \{x_1, x_2, x_3, x_4, y \mid \text{feedrate, spindle speed, cutting depth, cutting width, delta energy}\}$$

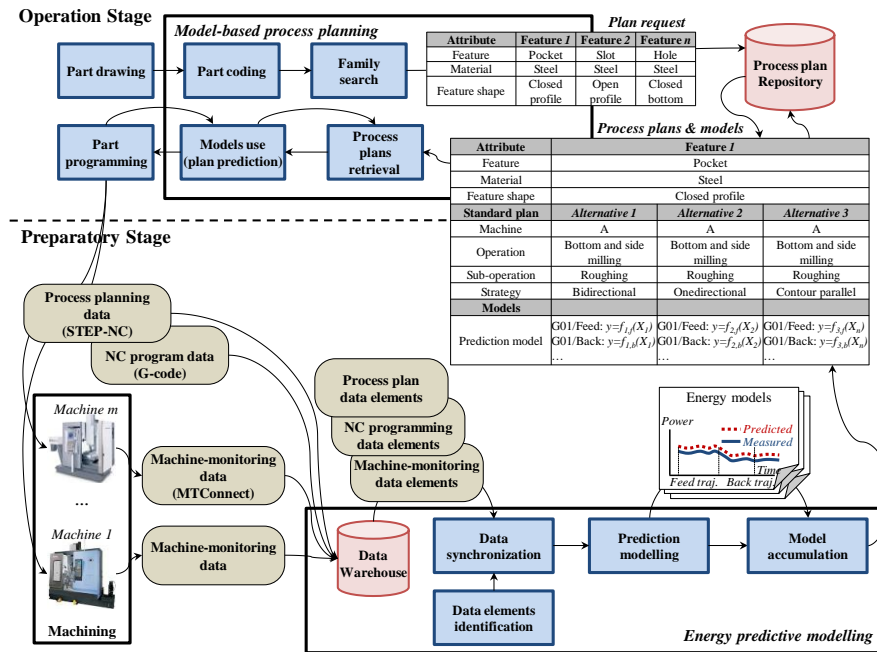


Figure 1. Concept of the proposed approach

3.2. Data synchronization

This function extracts and collects data element instances, and synchronizes machine-monitoring data with process plan and NC program data to generate training datasets for machine-learning analysis. These data instances are extracted from entities or attributes designated in machining data. We can extract *machine*, *material*, *operation*, *feature*, *strategy*, *feedrate*, *spindle speed*, *cutting depth* and *cutting width* from a STEP-NC part program; *command* and *trajectory* from an NC program; while, *delta energy* from an MTConnect document, which records sensor-level data about a machine's movements and actions [13]. As described in Section 3.1, the delta energy is indirectly acquired from *wattage* attribute in an MTConnect document.

Data synchronization comprises time and context synchronizations. Time synchronization aligns machining data instances on timestamps. Context synchronization configures input-and-output datasets aligning with sets of MC parameters. These synchronizations can be achieved by backward connection. The first connecting point is the *position* attribute in an MTConnect document. Each position instance can be matched with its corresponding NC block because this NC block obviously commands the tool movement associated with the position. Such NC block can be the next connecting point with a STEP-NC part program because NC blocks are generated based on the STEP-NC program where machining operations and tool path strategies are specified. In such way, training datasets can be prepared, formalized into $\{M: X, y\}$.

3.3. Energy modelling

This function generates energy models through machine-learning analysis that uses training datasets. Machine-learning analysis learns training datasets to acquire knowledge. This energy modelling relates to supervised learning because input and output variables are supervised by humans. This supervised learning derives a numerical function $y=f(X)+\varepsilon$ for an energy model through minimizing the error term (ε), which can be achieved by computing and adjusting appropriate coefficients repeatedly. Here, we use polynomial regression, which is commonly-used and applicable for

supervised learning. Figure 2 describes the structure of an energy model, which consists of a set of MC parameters and its corresponding energy function derived by regression.

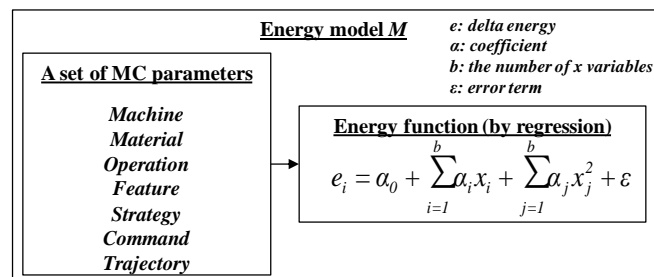


Figure 2. Structure of an energy model

3.4. Model accumulation

One problem of machine-learning analysis is that the models for the machining conditions that have not been run in machines cannot be created. It comes from the high dependency on training datasets, which do not exist in such machining conditions. For this case, this function creates alternative energy models based on existing energy models. Existing models can be reused to substitute for non-existent models through three kinds of methods: *cloning*, *blending* and *competition*.

Some machining strategies already own their energy models by the methods explained from Section 3.1 to Section 3.3, but other strategies may not own. Each strategy is composed of not only similar but also different tool paths with other strategies. For example, the feed path in bidirectional can be treated to be similar with that of unidirectional due to their similarity in cutting pattern and contact volume. This similarity allows to make correlations among strategies. Hence, we can prepare a correlation matrix, which records the mutual similarity in energy demands in terms of high, middle and low levels. These levels can be determined by preliminary energy analysis using machining data. High-level correlation has priority of creating alternative models than middle or low level correlation.

Figure 3 explains *cloning*, *blending* and *competition*. In Figure 3(a), *cloning* copies and pastes a high-level energy model. In Figure 3(b), *blending* chooses or synthesizes high-level models existent in multiple strategies. In Figure 3(c), *competition* selects the most-similar model when several high-level models exist in multiple strategies. This competition can be determined by likeliness or default setup. In such way, alternative energy models can be created for the machining conditions that do not own training datasets. Lastly, we can generate and accumulate machine-learned and alternative energy models in a knowledge base, *process plan repository*.

4. Methods for operation stage

Section 4 explains technical methods for individual functions in the operation stage, which consist of part coding, family search, process plans retrieval and models use. These methods build upon GT. Model-based process planning is possible through the integration of GT with the use of energy models.

4.1. Part coding

Once a part drawing is inputted, this function generates numerical codes, which identifies design attributes by numerical digits for efficient similarity search. A part can configure multiple sets of design attributes with respect to machining features. For problem simplification, we define the design attributes as below.

$$A = \{ a_1, a_2, a_3 \mid \text{feature, material, feautre shape} \}$$

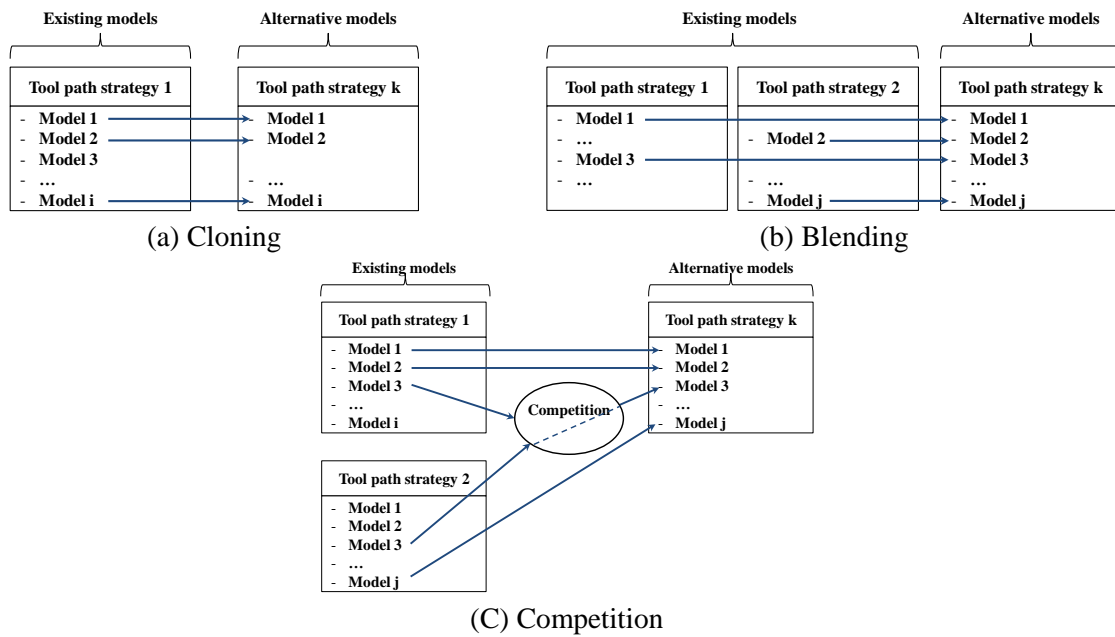


Figure 3. Methods of creating alternative models

4.2. Family search

This function searches the most-relevant process plan from the process plan repository by the input of the numerical digits. The similarity search can be applicable by the nearest neighbour search, which calculates Euclidean distance between an inputted case and existing cases [14], as expressed in Equation (1). We assume that all the weight factors are identical for problem simplification. Calculating similarity distances allows to find the most-similar process plan that scores the minimum distance in their similarities.

$$Similarity(a_i, a_e) = \sqrt{\sum_{i=1}^m w_i (a_i - a_e)^2} \quad (1),$$

where, a_i : an inputted case, a_e : an existing case, m : the number of attributes, w : weight factor

4.3. Process plan retrieval

This function retrieves the most-similar process plan found from the process plan repository. The process plan information contain machine, (sub-) operation and strategy, as showed in Figure 4. Moreover, the retrieved process plan directly links with energy models for model-based process planning. In Figure 4, Alternatives 1 and 2, respectively, suggest two selective bidirectional and contour parallel strategies.

4.4. Models use

This function allows process planners to anticipate energy values during their process planning and part programming. Once process planners decide tool path movements and generate an NC program, sets of MC parameters are fully identifiable aligning with a sequence of tool paths. Thus, energy models can be combined with regard to sequential sets of MC parameters. Each energy model can calculate a predicted energy value whenever process parameters are inputted. In such way, the total energy consumed during the execution of an NC program can be calculated through summing each area bounded by a moving time and a predicted energy value. The moving time on a tool path can be obtained from the path length divided by cutting speed.

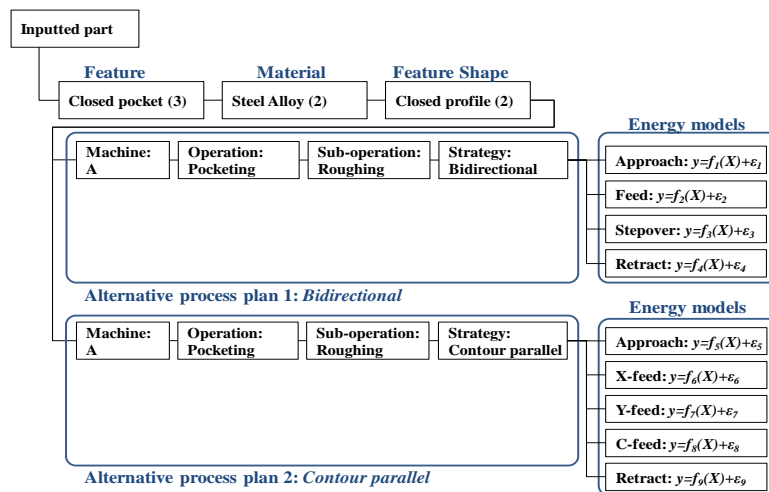


Figure 4. An example of standard process plan and energy model retrieval

5. Case study

5.1. Experiment

Table 1 lists twelve sets of process parameters for fabricating twelve parts that contain thirteen machining features. Feedrate (x_1), spindle speed (x_2) and cutting depth (x_3) are randomly determined within allowable ranges, and identically assigned on each trial. Cutting width (x_4) is fixed as the cutting tool diameter. The experimental setup is as follows: machine (Mori Seiki NVD 1500 DCG), Computerized Numerical Controller (CNC) (Fanuc 0i), workpiece (steel 1018, 10.16*10.16*1.27cm), cutting tool (flat end mill, 8mm diameter, 4 number of flutes), and power meter (system insights high speed power meter).

We perform actual machining based on the experimental setup. We collect twelve pairs of STEP-NC and NC programs and their associating MTConnect documents. Machine (m_1) and material (m_2) are fixed as described above while operation (m_3), feature (m_4), strategy (m_5), command (m_6) and trajectory (m_7) vary in terms of the entities and attributes coded in individual STEP-NC and NC programs.

Table 1. List of process parameters

Trial	Feedrate (x_1) (mm/tooth)	Spindle speed (x_2) (RPM)	Cutting depth (x_3) (mm)
1	0.0127	1500	1.5
2	0.0127	2000	1.5
3	0.0127	1750	1.0
4	0.0229	1750	1.0
5	0.0127	1750	2.0
6	0.0178	1500	1.0
7	0.0178	2000	1.0
8	0.0178	2000	2.0
9	0.0178	1750	1.5
10	0.0076	1750	1.5
11	0.0152	1750	1.5
12	0.0127	1750	1.5

5.2. Data collection and synchronization

Machine-monitoring data (MTConnect documents) comes from two sources. The CNC generates data instances including position and NC block, depending on task processing or events. The power meter measures power at 100 Hz frequency, independently with the CNC. Time synchronization combines these data instances from the two sources on the same timestamps, specially merged at average 0.365 second intervals. Then, STEP-NC and NC data instances are synchronized with MTConnect data instances on the same time intervals. The context synchronization generates individual datasets with regard to sets of MC parameters, formalized into $\{M: X, y\}$.

In such way, we collect fifty-one datasets, which correspond to the number of total sets of MC parameters on twelve trials. For better performance in energy models, we carry out data cleaning. We exclude the erroneous power data instances null or less than 1500 watt. It comes from that the machine spends minimum 1500 watt during turned-on. We exclude power data instances lowermost 0.5% or uppermost 0.5% among the entire dataset. It causes from our outlier decision.

5.3. Energy prediction modelling

We generate fifty-one polynomial regression functions for energy models using KNIME, a data mining tool [15]. These models contain different coefficients in terms of m_3, m_4, m_5, m_6 and m_7 . Table 2 presents the comparison result between the measured and predicted energy values on the twelve trials. Here, Root Mean Square Error (RMSE) means the average difference between individual measured and predicted energy values; meanwhile, Relative Total Error (RTE) measures percentages of the total measured and predicted energy difference. It is observable that energy models make a good performance to anticipate energy values within absolute 1.08% RTE. It conjectures from that energy models are accurately learned to ensure the rigidity of prediction through decomposing energy mechanism granularly up to the level of tool paths.

Table 2. Comparison between measured and predicted energy

Trial	Measured energy (kJ)	Predicted energy (kJ)	RMSE (J)	RTE (%)
1	13980.5	13929.1	28.67	-0.37
2	11410.0	11442.1	29.72	0.28
3	19571.3	19494.0	23.62	-0.40
4	9859.9	9853.1	28.39	-0.07
5	9973.1	10037.9	34.50	0.65
6	13392.9	13444.0	25.30	0.38
7	11079.3	11111.9	26.26	0.29
8	6038.8	5973.8	41.10	-1.08
9	9764.7	9734.8	32.58	-0.31
10	19312.8	19329.6	21.82	0.09
11	10821.5	10903.4	30.12	0.76
12	12607.7	12557.4	29.98	-0.40

5.4. Model accumulation

We produced three closed pocket features by bidirectional and contour parallel strategies but not unidirectional nor contour bidirectional. Nevertheless, the energy models for the two latter strategies can be alternatively created using the method explained in Section 3.4. In Figure 5(a), the approach and retract tool paths on unidirectional can clone those from the common strategy. The linear feed path on unidirectional can chose that of bidirectional through competition (specifically, likelihood) because they have high-level correlation and make the closest tool path patterns. In Figure 5(b), the energy models for contour bidirectional can be created from those of bidirectional or contour parallel through blending.

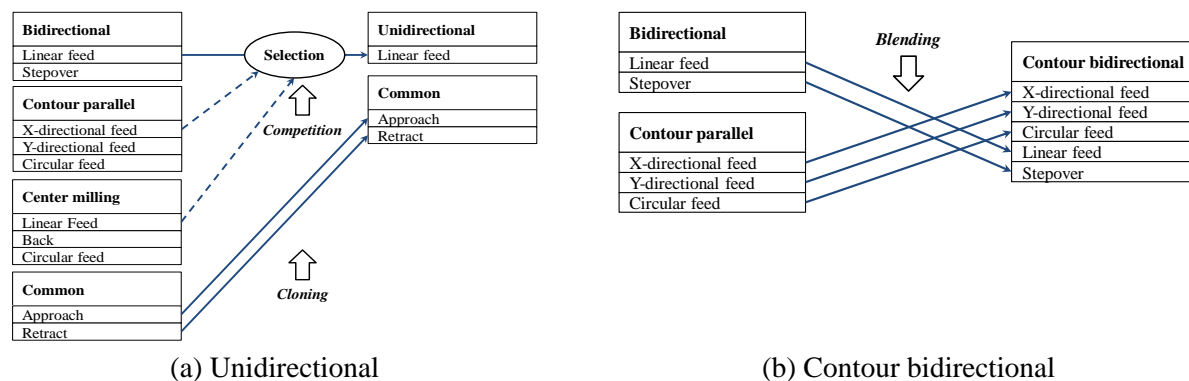


Figure 5. Cases of creating alternative models

6. Conclusion

This paper proposed a HPP-based process planning approach to enable energy prediction in the process planning phase through incorporating GPP and VPP. The proposed approach could create machine-specific models that can predict energy up to the level of tool paths, and use such energy models to implement model-based eco-process planning.

However, the present work has limitations. It only provides energy prediction models, but does not cover optimal process parameters for minimizing energy automatically. It excludes productivity performance including machining time and surface roughness, which are still significant in eco-process planning. We plan to advance the proposed approach toward multi-objective optimization through accommodating energy minimization and productivity performance.

7. Acknowledgments

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