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A Systematic Approach of Process Planning and Scheduling Optimization for Sustainable Machining

S. Wang, X. Lu, X.X. Li, W.D. Li†

Faculty of Engineering and Computing, Coventry University, Priory Street, Coventry, CV1 5FB, U.K.

†Corresponding author: E-mail: weidong.li@coventry.ac.uk, Tel: +44 (0)7557425332

Abstract

The lack of effective process planning and scheduling solutions for the sustainable management of machining shop floors, whose manufacturing activities are usually characterized by high variety and low volume, has been crippling the implementation of sustainability in companies. To address the issue, an innovative and systematic approach for milling process planning and scheduling optimization has been developed and presented in this paper. This approach consists of a process stage and a system stage, augmented with intelligent mechanisms for enhancing the adaptability and responsiveness to job dynamics in machining shop floors. In the process stage, key operational parameters for milling a part are optimized adaptively to meet multiple objectives/constraints, i.e., energy efficiency of the milling process and productivity as objectives and surface quality as a constraint. In the consecutive system stage, to achieve higher energy efficiency and shorter makespan in the entire shop floor, sequencing/set-up planning of machining features/operations and scheduling for producing multiple parts on different machines are optimized. Artificial Neural Networks are used for establishing the complex non-linear relationships between the key process parameters and measured datasets of energy consumption and surface quality. Several intelligent algorithms, including Pattern Search, Genetic Algorithm and Simulated Annealing, are applied and benchmarked to identify optimal solutions. Experimental tests indicate that the approach is effective and configurable to meet multiple objectives and technical constraints for sustainable process planning and scheduling. The approach, validated through industrial case studies provided by a European machining company, demonstrates significant potential of applicability in practice.

Keywords: Sustainable manufacturing, Computer Numerical Control machining, Process planning, Process scheduling, Intelligent algorithm, Machining feature

1. Introduction

Paramount demands for new products have increasingly incurred more manufacturing activities. In order to balance the multi-faceted dimensions of economic growth and environmental protection, a series of regulations and guidelines on lifecycle energy/carbon-related management have been developed in recent years for product design and manufacturing enterprises to embrace "Competitive Sustainable Development" (Jovane et al., 2008) and shoulder "Extended Producer Responsibilities (EPR)" (Mayers, 2007). For instance, the lifecycle carbon labeling scheme, outlined by the ISO 14040: 2006, ISO 14044: 2006 and Publicly Available Specification 2050 (PAS 2050), has been introduced with a bid to stimulate energy efficiency improvement and carbon emission reduction during product lifecycle. Among the various stages of product lifecycle, manufacturing processes are energy intensive making the stage one of the primary energy consumption and carbon footprint generation sources. Manufacturing processes in factories, in which motors, compressors and machine systems need to be powered, and adequate heating, ventilation and air conditioning equipment need to be maintained, contribute to over 24% of total European energy consumption (O'Driscoll and O'Donnell, 2013). Therefore, the effective implementation of manufacturing sustainability is prevalent. The roadmap research of intelligent manufacturing towards 2020, conducted by an international consortium consisting of researchers from Europe, Japan, Korea and the United States has summarized that the energy efficiency indicators of manufacturing on a national or sectional level have been defined, but sustainable process management solutions for single companies have not been effectively implemented, and the research is highly imperative (EU FP7 project IMS2020 (Bunse et al., 2011)). Machining such as milling is one of the important manufacturing processes. Co-operations between machining companies and their customers are more project-specific, customer-centric and flexible, the jobs/orders are likely to be diversified and many of them are urgent. As thus, there are many uncertainties and adjustment requirements in shop floors as part of the day-to-day operation planning in companies (Tolio et al., 2011). However, effective process planning and scheduling solutions, which are adaptive to dynamics in both the machining process and machine system levels, and multiple criteria like sustainability, product quality and productivity are systematically incorporated in the solutions, are lacking.

In order to address the above issue, an innovative approach of sustainable process planning and scheduling for machining multiple parts using multiple Computer Numerical Control (CNC) machines has been developed. The approach focuses on the milling process, and addresses dynamics in machining processes from the following two aspects: (1) it optimizes the key milling parameters of individual machines for producing individual parts to meet constraint-based multiple objectives, in terms of energy efficiency, surface quality and productivity; and (2) based on the optimized milling process parameters, an optimized solution of process sequencing, setting-up and scheduling for machining multiple parts using multiple candidate machines in a shop floor is achieved by considering the criteria of energy consumption and makespan of the machine system.

The innovations of the approach are summarized below:

- The approach provides a systematic, adaptive and efficient means to optimize machining companies' multi-objectives such as sustainability, productivity and makespan, and to meet technical constraints such as the required surface quality and precedence constraints among machining features/operations;
- Machining feature-based sustainable process planning and scheduling is highly desirable as machining features have been used as essential building blocks in modern Computer Aided Manufacturing (CAM) software. This approach supports intelligent decision making processes for feature-based sustainable process planning and scheduling, and based on that a practical way is paved for the approach to be integrated into modern feature-based CAM systems.

The rest of the paper is organized as follows. In Section 2, a literature survey on sustainable machining processes especially milling processes is given. In Section 3, the system framework of the research is presented. In Section 4, the constraint-based multi-objective optimization of key milling process parameters are presented. Based on the optimized parameters of individual machines for individual parts, the multi-objective optimization process of a machine system in a dynamic shop floor is described in Section 5. In Section 6, case studies and experimental tests are described. Finally the research is concluded in Section 7.

2. Related Work

In the past decades, research on manufacturing process planning and scheduling has been extensively conducted, and comprehensive surveys can be found from (Wang and Shen, 2010). This paper focuses on energy efficient process planning and scheduling, and the related state-of-the-art research is summarized below.

2.1 Energy consumption modeling based on key machining parameters

The European Machine Tool Builder Association indicates that the machine tool industry has shown strong interests on developing energy efficient manufacturing systems. To support the industry to achieve sustainability, a self-regulatory initiative for identification of measurements for energy performance and resource efficiency of machine tool systems has been proposed by the Association (Duflou et al., 2012). Aiming at implementing the initiative effectively, researchers have been actively investigating the energy consumption profile of machine tool systems during execution and identifying the key process parameters that affect the consumption profile. Based on that, optimization strategies are applied for process and system improvement in terms of energy saving.

Abele et al. summarized the total energy demand of a machine tool system during production as: $E_{total} = E_{th} + E_{additional} + E_{periphery}$, where E_{th} is the active energy theoretically needed to obtain the physical process effect, $E_{additional}$ and $E_{periphery}$ stand for the additional energy demands of the machine tool (e.g., energy to cover efficiency losses, or energy for machine functions such as central control) and peripherals (e.g., cutting fluid pump) respectively (Abele et al., 2005). Among the energy consumption of a machine tool system, the unit energy consumption demand of a machining process is remaining a challenging research issue. Gutowski et al. (2006) classified related energy consumption of manufacturing into the following categories:

- Fixed energy: energy demand of all activated machine components ensuring the operational readiness of the machine;
- Operational energy: energy demand to distinctively operate components enabling the cutting as performed in air-cuts;
- Tool tip energy: energy demand at tool tip to remove the workpiece material;
- Unproductive energy: energy converted to heat mainly due to friction during the material removal.

Series of research work were carried out to detail the energy profile for the aforementioned categories. A summary of the work is given in Table 1. Mori et al. (2011) developed an empirical model, in which several processes are considered such as positioning and acceleration of the spindle, tool changes, machining, and stop of the spindle. Newman et al. (2012) developed empirical models to establish the relationship between cutting parameters, such as depth of cut, feedrate and number of cuts, and power consumption. Two case studies of finish cutting and semi-finish cutting of Aluminum were used to verify the models. In Hu et al. (2012)'s work, a torque sensor was mounted onto the cutter and active power consumed by a machining process was calculated, while the total input power to the machine tool system was measured by a power sensor. Based on experimental data, an empirical model was established to estimate the total power and active power for machining, which are used to support the on-line monitoring system. The Taguchi method was introduced to analyze the relationship among cutting parameters, energy consumption, and surface roughness in order to determine the suitable cutting parameters leading to the minimum energy consumption and the best surface roughness (Camposeco-Negrete, 2013). A Grey Relationship Analysis method was developed for establishing relationships among Material Removal Rate (*MRR*), machining power and surface roughness minimization, the Response Surface Methodology (*RSM*) and the Taguchi method were used for factor effect analysis (Yan and Li, 2013). Winter et al. (2014) investigated the energy performance of a grinding process. The Sensitivity Analysis method was applied to illustrate how cutting parameters, including cutting depth, cutting speed and dressing speed affect the energy consumption in order to achieve multi-objective optimization.

Table 1: Energy consumption models for machine tool systems.

Works	Input variables						Optimization objectives				Research analysis methods
	Depth of cut	Spindle speed	Cutting speed	Width of cut	Chip load	M-features	Cutting power	Surface roughness	Processing time	Other	
Mori et al., 2011		x	x	x			x				Empirical models for case studies of cutting condition changes and deep hole drilling
Avram and Xirouchakis, 2011	x	x	x	x		x	x				Empirical models for usage stages of machining
Kong et al., 2011	x	x	x	x		x	x		x		Empirical models for start-up, idle and usage stages of machining
Newman et al., 2012		x	x		x		x		x		Empirical models and two case studies on semi-finish and finishing machining
Hu et al., 2012	x	x	x				x				Least Square Method (LSM) for machining
Balogun and Mativenga, 2013	x	x	x	x			x				Empirical models for start-up, idle and usage stages of machining
Camposeco-Negrete, 2013	x	x	x				x	x			Orthogonal array, signal to noise (S/N) ratio and analysis of variance (ANOVA)
Yan and Li, 2013	x	x	x	x			x	x			Grey Relationship Analysis, Response Surface Methodology (RSM) and the Taguchi method
Wang et al., 2013	x	x	x	x			x				Empirical models for machining shop floor
Dai et al., 2013	x	x	x	x				x			A hybrid Genetic Algorithm for sustainable machining optimization
Winter et al., 2014	x		x				x	x		x	Sensitivity Analysis method
Aramcharoen and Mativenga, 2014						x	x		x	x	Assessment of alternative tool-paths, identified major opportunities for energy reduction

2.2 Energy consumption modeling based on Specific Energy Consumption

The method of the above research is to design and conduct experimental tests to reveal the underlying relationship between the energy performance of a machine tool system and key cutting parameters, qualitatively and quantitatively. Another group of research focuses on developing empirical models based on *MRR* and Specific Energy Consumption (*SEC*) to model and estimate the unit process energy consumption of a machining process. The related work is summarized in Table 2. The most representative model was developed by Gutowski et al. (2006). The specific energy requirements for manufacturing processes, i.e., *SEC,* were modeled as a function of *MRR* in an energy framework. *SEC* is defined as the energy consumption in cutting 1 cm^3 material. However, in the model, the specifications for the fixed power P_0 and the constant k were not given. To improve this model, researchers developed enhanced energy consumption models. For instance, Li and Kara (2011) used an empirical modeling approach to develop a unit process energy consumption model to characterize the relationship between *SEC* and machining parameters, and the coefficients in the model were decided through experimental tests.

Furthermore, the empirical approach was applied to turning, milling and grinding processes on different machine tools, Kara and Li (2011) focused on turning process while Li et al. (2012) focused on grinding process. Similarly, a case study of a micromachining center was developed by Diaz et al. (2011) to model the *SEC* in cutting. This model further confirms the relationship between the energy consumption and *MRR*. In addition, Li et al. (2013) adopted a hybrid modeling method based on thermal equilibrium and empirical modeling to characterize the relationship between process variables and energy consumption for milling processes and experimental tests were conducted to identify the energy-related coefficients for a specific machine. Yan and Li (2013) developed the Grey Relational Analysis method to model the relationship between multi-objectives (including energy consumption, production rate and cutting quality) and key machining parameters (including spindle speed, feedrate, depth of cut and width of cut). Meanwhile, the Taguchi method was applied to analyze the influence of machining parameters on the multi-objectives in a qualitative way in order to identify a trade-off among the energy consumption, production rate and cutting quality based on different combinations of machining parameters.

Table 2: *SEC*-based energy models for machining processes.

Works	Model or methods
Gutowski et al., 2006	$SEC = P_0/v + k$ Where P_0 is the fixed power and k is a constant with units of kJ/cm^3, v is the rate of material processing in cm^3/sec.
Kara and Li, 2011	$SEC = C_0 + C_1/MRR$ Where the coefficients C_0 and C_1 are different among different machine tools and needed to be experimentally determined; *MRR* is the material removal rate.
Diaz et al., 2011	$SEC = k/MRR + b$ Where the constant k is related to the unit of power and b represents the steady-state specific energy.
Li et al., 2013	$SEC = k_0 + k_1 \cdot n/MRR + k_2/MRR$ Where k_0 is the specific energy requirement in cutting operations, k_1 is the specific coefficient of spindle motor, k_2 is the constant coefficient of machine tools and equals the sum of standby power and the spindle motor's specific coefficient; n is the spindle speed in rounds/second.

2.3 Energy consumption modeling based on CNC codes

The set of CNC codes can describe an entire machining process and the working process of the related accessory equipment, and therefore, the entire energy profile can be modeled and estimated. Based on the tool paths from CNC codes (e.g., G-code), the energy consumption assessment for the spindle axis, feed axis and load/unload cycle were formulated (Avram and Xirouchakis, 2011). Based on an established energy consumption model from tool paths, a Web-based system was developed for environmental sustainability monitoring and evaluation (Kong et al., 2011). In the system, tool path generation strategies for different machining features were modeled in terms of energy consumption. Based on CNC codes, an energy assessment framework for machining workshop was built up (He et al., 2012). The energy consumption framework consists of four layers, i.e., workshop layer, task layer, manufacturing unit layer and machine tool layer. In each layer, major elements affecting energy consumption were considered. In the machine tool layer, machining tasks are executed and the primary energy consumption comes from a machining workshop. In the manufacturing unit layer, the layout and sequence of a set of machine tool systems are designed. The task layer and workshop layer are mainly for particular task's planning and scheduling, and the venue for the manufacturing tasks to take place, in which electricity, heating, ventilation and air-conditioning equipment are the major energy consumption units. In the machine tool system, cutting force, cutting velocity, cutting depth and feedrate were used as inputs to establish an empirical model for energy consumption estimation during machining. Some calculation processes in these works are summarized in Table 3.

Table 3: CNC-based energy models for machining processes.

Focus	Model and methods
Avram and Xirouchakis, 2011	$E = E_{as} + E_{run} + E_{cut} + E_{ds} = \int_{t0}^{t1} P_{as}dt + \int_{t1}^{t3} P_{run}dt + \int_{t2}^{t3} P_{cut}dt + \int_{t3}^{t4} P_{ds}dt$, where E_{as} and P_{as} are the energy and power requirements for spindle respectively, E_{run} and P_{run} are the energy and power requirements for the motors before engaging the material cutting, E_{cut} and P_{cut} are the energy and power requirements for the material cutting, and E_{ds} and P_{ds} are the energy and power requirements on spindle unloading; t_0, t_1, t_2, t_3, t_4 are the time spent on the above stages respectively.
Diaz et al., 2011	$E = P_{avg} * \Delta t = (P_{cut} + P_{air}) \cdot \Delta t$, where P_{avg} is the average power demand and composed of a cutting power P_{cut} and air cutting power P_{air}; Δt is the processing time.
Kong et al., 2011	$E_{machining} = E_{const} + E_{run-time} + E_{cut}$, and $E_{cut} = K_{cut} \cdot w \cdot b \cdot z^p \cdot v_f^{1-p} \cdot n^p$, where $E_{machining}$, $E_{run-time}$ and E_{cut} represent the total energy of machining process, constant energy consumed by the functions that are not directly related to the machining, run-time energy consumed by a spindle, machine axes and tool changer, and energy consumed by the material removal action of a machine tool, respectively. v_f is the feedrate, n is the spindle speed, w is the width of cut, z is the number of flutes of a cutter, p and K_{cut} are empirically determined fitting constants.
Mori et al., 2011	$E = P_1 * (T_1 + T_2) + P_2 \cdot T_2 + P_3 \cdot T_3$, where P_1, P_2 and P_3 are constant, corresponding to the power demand of cutting, positioning the work and accelerating/decelerating the spindle to a specified speed, T_1, T_2 and T_3 are the corresponding times.
He et al., 2012	$E = E_{spindle} + E_{feed} + E_{tool} + E_{cool} + E_{fix}$, where $E_{spindle}$, E_{feed} , E_{tool} , E_{cool} and E_{fix} represent the energy consumed by spindle, feed, tool, cool and fix.
Newman et al., 2012	$E = P/fhD$, where E and P are the energy and power requirements for the milling process respectively, f, h and D stand for feedrate, depth of cut and diameter of cutter respectively.
Balogun and Mativenga, 2013	$E = P_b \cdot t_b + (P_b + P_r) \cdot t_r + P_{air} \cdot t_{air} + (P_b + P_r + P_{cool} + k \cdot v) \cdot t_c$, where P_b, P_r, P_{cool} and P_{air} represent the basic and ready state powers, coolant pumping power requirements and the average power requirements for a non-cutting approach and retract moves over the component respectively, t_b, t_r, and t_c are the basic, ready and cutting times respectively, t_{air} represents the total time duration of the non-cutting moves; k with units of kJ/cm^3 is the specific cutting energy, v in cm^3/s is the rate of material processing.

Though a large amount of research works have been reported as above, the following research issues are highly expected for further investigation:

- Modern machining software packages have adopted machining features as essential building blocks, and the energy consumption assessment associated with machining features and the process parameters will be more effective to support decision making in sustainable process planning and scheduling. Research on machining feature-based sustainable process planning was still preliminary, , further research is imperative to understand the characteristics of energy consumption influenced by machining features/operations and key process parameters;
- Many of the above research works are still preliminary and energy efficiency has not been systematically addressed in process planning and scheduling in a dynamic shop floor. It is critical to develop systematic, adaptive and efficient approaches to address multiple performance criteria and technical constraints such as productivity, surface quality, makespan and precedence constraints among machining features/operations from both the process level and the system level.

3. System Framework

Some essential considerations in process planning and scheduling are (Li et al., 2006):

- Generating optimized process parameters of a part machined on a machine to meet desired functional specifications and achieve good manufacturability;
- Determining the machining feature/operation sequence, set-up plan and schedule according to performance criteria and precedence constraints. Process sequencing means a set of machining features/operations will be sequenced according to some performance criteria such as productivity and quality and constrained by some technical or geometrical precedence constraints among machining features/operations. A set-up can be generally defined as a group of features/operations that are manufactured on a single machine using the same fixture. The scheduling task is to assign the parts and their machining features/operations to specific machines to be executed in different time slots, targeting at good shop floor performance, such as the shortest makespan and the total lowest energy consumption in the shop floor.

In a dynamic machining situation, a part can be manufactured using different process parameters and on different candidate machine systems, which generate different process plans and schedules. In summary, a group of alternative process plans and schedules can be generated using three strategies: machine tool flexibility, process sequencing and setting-up flexibility, and schedule flexibility (Li and McMahon, 2007). Machine tool flexibility refers to the possibility of performing a feature/operation on alternative machine tool systems. Process sequencing and setting-up flexibility corresponds to the possibility of changing the sequence and set-up in which the features/operations are performed. Meanwhile, for a group of parts, alternative schedules can be created based on scheduling flexibility, which relates to the possibility of arranging different schedules to manufacture the features/operations of the parts to achieve the shortest makespan, lowest energy consumption and/or better performance for other shop floor indicators.

A Gantt chart has been popularly used to represent a schedule of a group of parts, as illustrated in Figure 1. In the Gantt chart, the order in which the parts and their operations are carried out is laid out and the dependencies of the tasks are managed. The X-axis of the Gantt chart represents time. Each row in the Y-axis represents a machine and the specific arrangement of the operations of the parts on the machine. A machine is comprised of a number of time slots, which can be further classified into idle time slots, preparation time slots for machining operations (further including the set-up time and/or the tool change time), and machining time slots of operations.

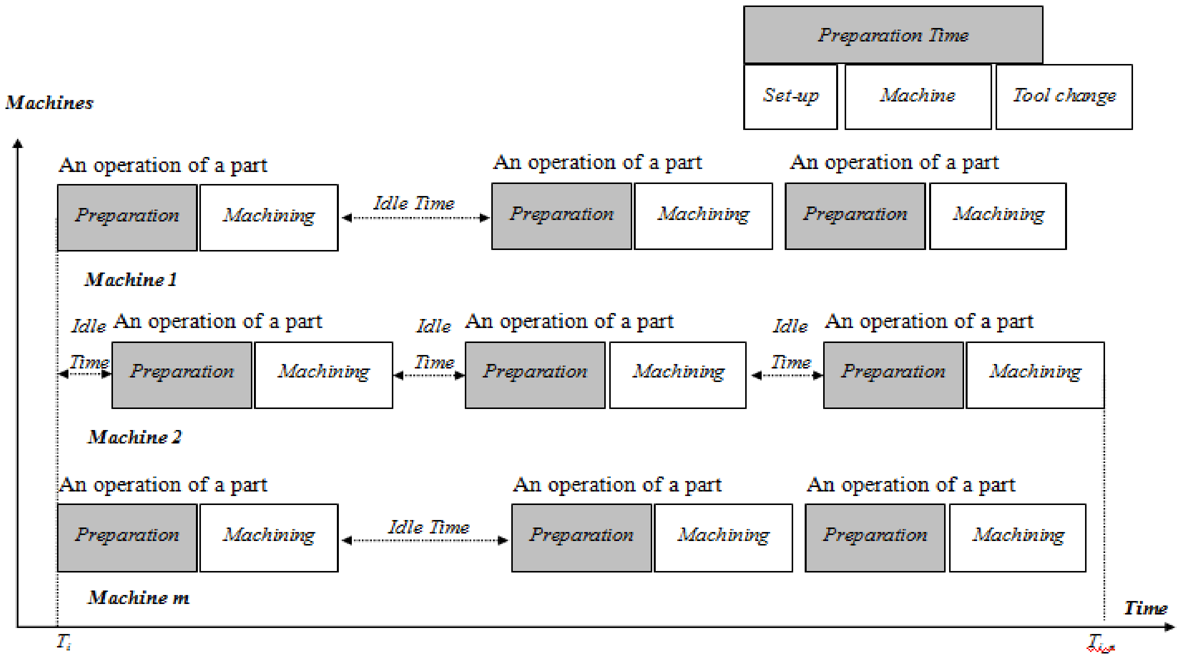


Figure 1: A Gantt chart for scheduling parts and their machining features/operations.

Based on the above, in this research, a two stage optimization approach is proposed, detailed below (illustrated in Figure 2):

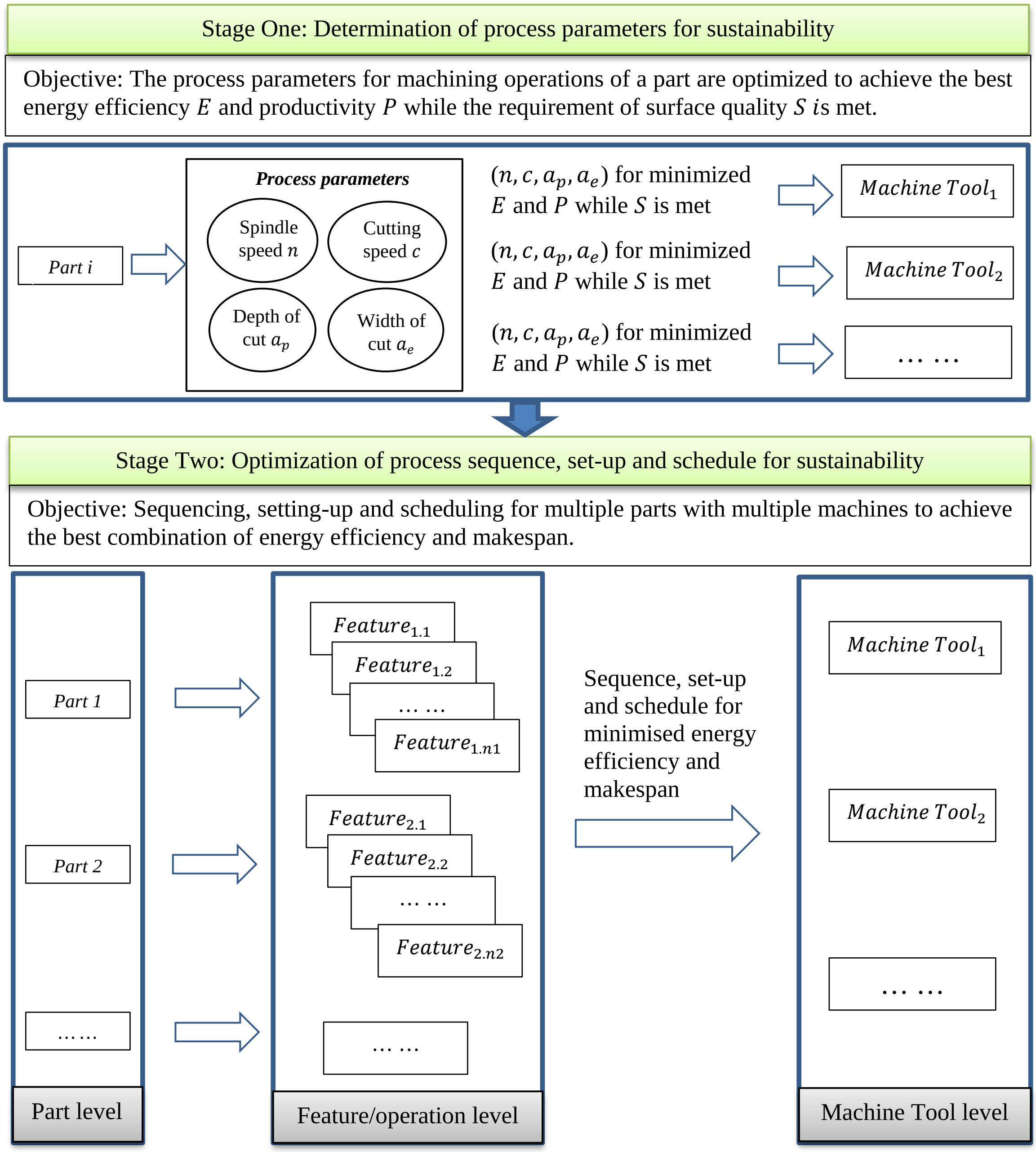


Figure 2: Two stages of sustainable process planning and scheduling optimization.

(1) The first stage is to optimize the key parameters of a milling process for a part in a single machine to achieve a better energy efficiency and productivity while the surface quality requirement is met. These performance indicators in machining, i.e., energy efficiency for production, surface quality and productivity, are incorporated into a constraint-based multiple objective optimization problem, while critical process parameters affecting the performance indicators, including spindle speed, cutting speed, depth of cut and width of cut, are taken into account as variables to support the above optimization modeling and processing. The relationships between the variables and the energy efficiency/surface quality could be highly nonlinear. As thus, Artificial Neural Networks (ANNs) are employed in order

to present the nonlinear relationship among the variables and performance indicators adaptively and effectively. Intelligent algorithms are applied to identify optimized process parameters for individual parts on individual machines;

(2) Based on the above optimized results of individual machines for individual parts, the second stage of the approach is to identify optimized process sequence, set-up and schedule with multiple machines for manufacturing multiple parts. In this research, the energy efficiency and makespan of a machine system are integrated as multiple optimization objectives, and precedence constraints among features/operations are considered. Intelligent algorithms are then applied to determine an optimized process plan and schedule. In order to effectively generate a comprehensive search space to support the optimization processes, the aforementioned three strategies, i.e., machine tool flexibility, process sequencing and setting-up flexibility and scheduling flexibility, are used for the generation of alternative process plans and schedules as a feasible search space to support the above optimization process.

4. Process Parameter Identification for Sustainability

Key parameters in milling, such as spindle speed, cutting speed, depth of cut and width of cut, affect the performance of a milling process, such as energy consumption, surface quality and productivity. In the following, based on the relationship between the key process parameters and the performance of a milling process, a normalization process and an optimization process have been developed to ensure good machining process in terms of energy efficiency, surface quality and productivity.

4.1 Process of parameter identification

Milling, which is a primary process in machining, is considered in this research. The energy performance, surface quality and productivity of a machining process can be evaluated using three indicators, i.e., Energy consumption (E), Surface roughness (S) and Machining Removal Rate (MRR). These indicators interlace each other, and a better performance of one indicator could need tradeoff of the other indicators (Yan and Li, 2013). On the other hand, key parameters of a milling process including spindle speed (n), cutting speed (c), depth of cut (a_p) and width of cut (a_e) affect these performance indicators significantly.

Given the Surface roughness S is pre-decided by users as a constraint, optimization of Energy consumption E and Machining Removal Rate MRR are modeled as a constraint-based multi-objective optimization problem, and the four process parameters (n, c, a_p, a_e) are considered as variables in the optimization problem. The target is to obtain optimized multi-objectives E and MRR while the pre-set S (denoted as μ) as a constraint is met. Upon the completion of optimization, the values of (n, c, a_p, a_e) within their working ranges, which meet the above optimized objectives and constraint, are identified. In the process, ANNs have been constructed for representing the relationships between (n, c, a_p, a_e) and S, and between (n, c, a_p, a_e) and E, respectively. The Grey Relationship Analysis approach has been employed to normalize E and MRR in the formation of a multiple-objective target function. Several optimization algorithms have been applied for identifying the optimal values of the indictors and process parameters. The process is illustrated in Figure 3, and the details are explained below.

4.2 Representation of Energy consumption (E), Surface roughness (S) and Machining Removal Rate (MRR), and their grey relational analysis processes

In order to develop an optimization model of a machining process, spindle speed (n), cutting speed (c), depth of cut (a_p) and width of cut (a_e) are used to represent Energy consumption (E), Surface roughness (S) and Machining Removal Rate (MRR). In this research, the units for spindle speed, cutting speed, depth of cut and width of cut, Energy consumption, Surface roughness and Machining Removal Rate are rounds/minute (RPM), mm/minute, mm, mm, kilo-Joules (KJs), µm, and mm^3/minute, respectively.

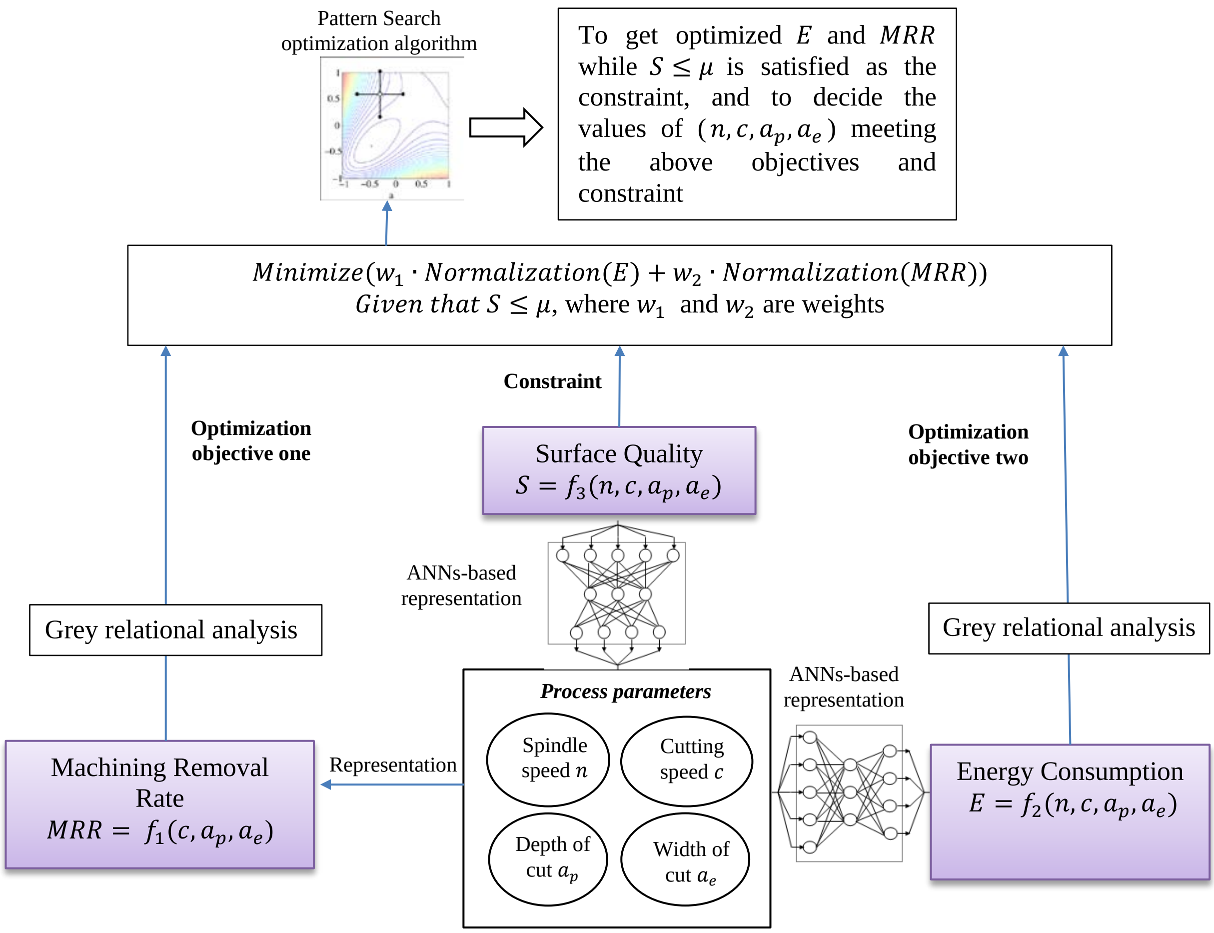


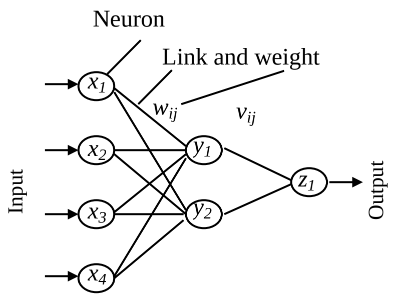
Figure 3: Optimization of milling indicators and process parameters.

The MRR for a milling process can be calculated below:

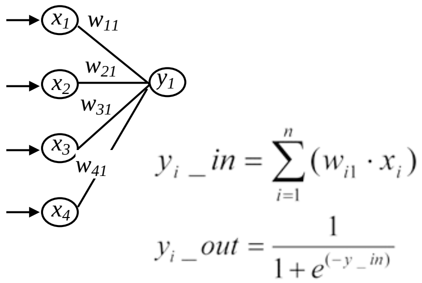
$$MRR = c \cdot a_p \cdot a_e \tag{1}$$

The relationship between the process parameters and Energy consumption (E) or Surface roughness (S) is highly nonlinear and an analytical solution is not easy to extract. In this research, the representation of E or S between the measured data set of (n, c, a_p, a_e) is constructed using a Multi-Layer Feed-Forward (MLFF) ANNs trained using a Back-Propagation (BP) algorithm (shown in Figure 4). ANNs offer several valuable characteristics: (1) The ability to capture and represent complicated input/output relationships; (2) no prior knowledge about the input and output mapping is required for the model development. Unknown relationships are inferred from the data provided for training. Therefore, with ANNs, the fitting function is represented by the networks and does not have to be explicitly defined; and (3) the ability for generalization, meaning they can respond correctly to new data that have not been used for the ANNs model development (Li et al., 2006).

The Grey Relational Analysis process (Tzeng et al., 2009) consists of two steps. The first step is the normalization of the original sequences in the range between zero and one, and the second step is to calculate the grey relational coefficient to express the relationship between the ideal and actual normalized experimental results. Details are described below.



(a) A three-layer neural networks



(b) Computation for neurons

Figure 4: Multi-Layer Feed-Forward ANNs for Energy Consumption and Roughness representation.

(1) Normalization:

Since the final optimization is to find the minimal value of objective function which is the sum of the grey relational coefficients of E and MRR, and the expectancy of energy consumption E is the smaller the better, the original sequence of E_i should be normalized as:

$$Z'_i = \frac{E_i - min(E_i)}{max(E_i) - min(E_i)} \tag{2}$$

where $E_i (i = 1,2, \dots, n)$ is the energy value of a sample in an experimental set, and n is the number of the experimental set; On the contrast, the expectancy of productivity MRR is the larger the better. The original MRR should be normalized as:

$$Z''_i = \frac{max(MRR_i) - MRR_i}{max(MRR_i) - min(MRR_i)} \tag{3}$$

where MRR_i $(i = 1,2, \ldots, n)$ are the MRR values of a sample in an experimental set, and n is the number of the experimental set.

(2) Calculation of the grey relational coefficients for E and MRR:

$$GRC_j = \frac{\Delta_{min} + w \cdot \Delta_{max}}{\Delta_j + w \cdot \Delta_{max}} \tag{4}$$

where $\Delta_j = \|Z_0 - Z_j\|$, $\Delta_{min} = \min_{1 \le j \le n} \Delta_j$, $\Delta_{min} = \max_{1 \le j \le n} \Delta_{j,}$ and $w \in [0\ 1]$. Usually $w = 0.5$ is used.

4.3 Optimization process

The optimization objective is modeled using the grey relational coefficients as below:

$$\begin{cases} min(w_1 \cdot GRC_E + w_2 \cdot GRC_{MRR}),\ S \le \mu \\ min(w_1 \cdot GRC_E + w_2 \cdot GRC_{MRR} + (s/\mu - 1) \times 100),\ S > \mu \end{cases} \quad w_1 + w_2 = 1 \tag{5}$$

The constraint: $S \le \mu$ (μ the user defined surface roughness) is modeled in the objective function as a penalty

Bounds: the upper and lower bounds of input variables (n, c, a_p, a_e) are limited by the maximum and minimum values of the measurement samples

$MRR = f_1(c \cdot a_p \cdot a_e)$, $E = f_2(n, c, a_p, a_e)$ *and* $S = f_3(n, c, a_p, a_e)$

w_1 and w_2 are the user defined weights for Energy consumption and Productivity respectively. For instance, if only Energy consumption is concerned, then set $w_1 = 1$ and $w_2 = 0$. Usually both indicators are taken into account by setting balanced weights with $w_1 = 0.5$ and $w_2 = 0.5$. A set of optimization algorithms, including Pattern Search, Genetic Algorithm and Simulated Annealing algorithm, are applied to this problem. Optimization results show that the Pattern Search method exhibits a better computational efficiency and a more reliable optimization performance for this case. Thus, the Pattern Search method is introduced herewith. Pattern Search belongs to direct search for solving optimization problems that does not require the gradient of the objective function. It would iterate from search, polling and expanding/contracting processes until the optimal result is found. The detailed procedure is:

1. Choose an initial vector point $\boldsymbol{x_0}$ and define the pattern vectors. For a problem with four input variables, there are total eight pattern vectors as: $v_1 = [1\ 0\ 0\ 0] \cdots v_4 = [0\ \ 0\ 0\ 1], v_5 = [-1\ 0\ 0\ 0] \cdots v_8 = [0\ 0\ 0\ -1]$;

2. Search for a mesh point x_i around x_0 that has a less objective function compared to x_0. The search mesh is generated as $x_i = x_0 + \Delta_i$, where $\Delta_i = \Delta m \cdot v_i$, Δm is the current mesh size, the upper and lower bounds for each variables are to be checked;
3. If a better solution x is found, the poll is successful, update the vector point $x_0 = x$ and increase the mesh size: $\Delta m = 2 \cdot \Delta m$, otherwise, keep the original x_0 and reduce the mesh size: $\Delta m = 0.5 \cdot \Delta m$;
4. Check if any of the stop conditions (the mesh size is less than mesh tolerance or the difference between the function value at the previous best point and at the current best point is less than the value of function tolerance) is met, if yes, stop the optimization. Otherwise, go to Step 2.

5. Sustainable Optimization for Machining Systems

There are alternative sequences and set-ups between machining features/operations, and a group of machines available as candidate resources for scheduling. In the following, the energy consumption modeling for features/operations in a manufacturing system is built, followed by an optimization process for the model. During the processes, the sequences of machining features/operations are constrained by some technical or geometrical requirements of parts, which are handled in the optimization process by introducing a penalty function (Li et al., 2006).

5.1 Energy consumption modeling

For a machine, its energy power profile is illustrated in Figure 5, which consists of startup phases, idle/change phases, working phases (operation), and shutdown phases. Hence, the energy consumption of a machine can be separated into the corresponding four segments.

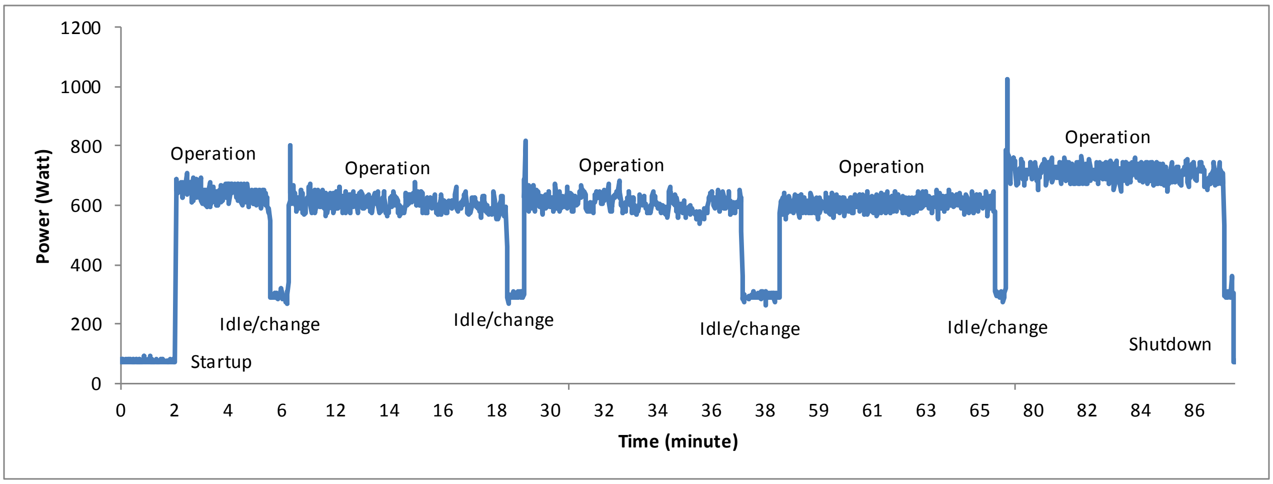


Figure 5: Different phases of energy consumption of operations in a machine.

The energy consumption during the idle phase can be formulated as:

$$E(M_i)_{idle} = P_{idle}(M_i) \cdot T_{idle}(M_i) \tag{6}$$

where $E(M_i)_{idle}$ stands for the energy consumption of the idle phase of the i^{th} machine; $P_{idle}(M_i)$ is the power demand of the i^{th} machine during the idle phase, which is the sum of the power demand of all the components in the machine and usually a constant value for the particular machine; $T_{idle}(M_i)$ stands for the total idle time of the i^{th} machine, which can be represented as:

$$T_{idle}(M_i) = \sum_{j=1}^{n} T_{j,j+1}\,(O_{j,i}, M_i) \tag{7}$$

where n stands for the number of the operations denoted as $O_{j,i}$ to be executed on the i^{th} machine; $T_{j,j+1}(O_{j,i}, M_i)$ stands for the idle time between the j^{th} and $(j+1)^{th}$ operations to be executed on the i^{th} machine. $T_{j,j+1}(O_{j,i}, M_i)$ can be obtained using the following pseudo codes.

If $T_{j.end}(O_{j,i}, M_i) < T_{j+1.start}(O_{j+1,i}, M_i)$ then

// The j^{th} operation ends before the $(j+1)^{th}$ operation

// Operation and the machine will be idle

$T_{j,j+1}(O_{j,i}, M_i) = T_{j+1.start}(O_{j+1,i}, M_i) - T_{j.end}(O_{j,i}, M_i)$

Else // There is no waiting

$T_{j,j+1}(O_{j,i}, M_i) = 0$

Endif

Here, $T_{j.end}(O_{j,i}, M_i)$ and $T_{j+1.start}(O_{j+1,i}, M_i)$ stand for the end time of the j^{th} operation and the start time of the $(j+1)^{th}$ operation respectively.

The energy consumption during the working phase can be represented as:

$$E(M_i)_{.working} = \sum_{j=1}^{n} E_j(O_{j,i}, M_i)_{.working} \tag{8}$$

where $E(O_{j,i}, M_i)_{.working}$ stands for the energy consumption of the working phase for the i^{th} machine; n stands for the number of the operations denoted as $O_{j,i}$ to be executed on the i^{th} machine; $E_j(O_{j,i}, M_i)_{.working}$ stands for the energy consumption of the j^{th} operation on the i^{th} machine.

The energy consumption of the tool change phase can be computed as:

$$E(M_i)_{.tool\_change} = P_{idle}(M_i) \cdot T_{tool\_change}(M_i) \tag{9}$$

where $E(M_i)_{.tool\_change}$ represents the energy consumed during the tool change phase; P_{idle} is the idle power needed during the machine waiting phase for this tool change on the i^{th} machine; $T_{tool\_change}(M_i)$ stands for the total tool change time on the i^{th} machine in total, which can be represented as:

$$T_{tool\_change}(M_i) = \sum_{j=1}^{m} T_{tool\ \ change}(O_{j,i}, M_i) \tag{10}$$

where m stands for the number of the tool changes on the i^{th} machine; $T_{tool\ \ change}(O_{j,i}, M_i)$ stands for the tool change time for an operation $(O_{j,i})$.

The energy consumption of the set-up phase can be computed as:

$$E(M_i)_{.set-up} = P_{idle}(M_i) \cdot T_{set-up}(M_i) \tag{11}$$

where $E(M_i)_{.set-up}$ represents the energy consumed during the set-up phase; $P_{idle}(M_i)$ is the idle power needed during the machine waiting phase for this set-up; $T_{set-up}(M_i)$ stands for the total set-up time on the i^{th} machine, which can be represented as:

$$T_{set-up}(M_i) = \sum_{j=1}^{p} T_{set-up}(O_{j,i}, M_i) \tag{12}$$

where p stands for the number of the set-up on the i^{th} machine; $T_{setup}(O_{j,i}, M_i)$ stands for the set-up time for an operation $(O_{j,i})$ on the i^{th} machine.

Based on the energy consumption of the above phases, the total energy consumption of a machine can be represented below:

$$E(M_i) = E(M_i)_{idle} + E(M_i)_{.working} + E(M_i)_{.tool\_change} + E(M_i)_{.set-up} \tag{13}$$

where $E(M_i)$ stands for the total energy consumption of the i^{th} machine.

Therefore, if there are n machines to be used in the process planning and scheduling, the overall energy consumed by all the machines to machine all the parts is:

$$E_{total} = \sum_{i=1}^{n} E(M_i) \tag{14}$$

Makespan means the maximum interval time spent to machine all the parts. It can be defined in the following:

$$Makespan = max(T(M_i)) \tag{15}$$

where $T(M_i)$ is the time interval between the stop time of the i^{th} machine and the start time of the entire job. It includes the start time and utilization time of the i^{th} machine, which includes idle, working, tool change and set-up phases. That is, $T(M_i)$ can be represented as:

$$T(M_i) = T_{start}(M_i) + T_{idle}(M_i) + T_{working}(M_i) + T_{tool\_change}(M_i) + T_{set-up}(M_i) \tag{16}$$

5.3 Optimization process

As the two different objective functions, i.e., total energy and makespan, can have very different magnitudes, normalization of the two objective functions is required prior to the optimization of the weight summed objective function. Unlike the optimization of milling parameters in terms of energy consumption E and productivity MRR described in Section 4.2, which maximum and minimum values are already known, the maximum and minimum values of these two objective functions are unknown before optimization. In this case, a suitable normalization schema that normalizes the objective functions by the differences of objective functions in the Nadir and Utopia points is employed (Mausser, 2006). The Utopia point z_i^U provides the lower bound of the i^{th} objective function and can be obtained by minimizing the i^{th} objective function individually, i.e.,

$$z_i^U = f_i(x^i) = min\{f_i(x)\} \tag{17}$$

The upper bound is then obtained from the Nadir point z_i^N , which is defined as

$$z_i^N = f_i(x^k) = max_{1 \ll j \leq I}\{f_i(x^j)\} \tag{18}$$

where I is the total number of objective functions.

This normalization schema may be computationally expensive when the problem dimension is very large. For this research, the time spent on this calculation is acceptable as the number of optimization parameters is not very large. Hence, the energy consumption and timespan are to be normalized individually as:

$$\begin{cases} NE = (E_{total} - z_1^U)/(z_1^N - z_1^U) \\ NT = (Makespan - z_2^U)/(z_2^N - z_2^U) \end{cases} \tag{19}$$

The objective function is calculated as weighted sum of the two objectives:

$$\textit{Objective: } min(w_1 \cdot NE + w_2 \cdot NT), \quad w_1 + w_2 = 1 \tag{20}$$

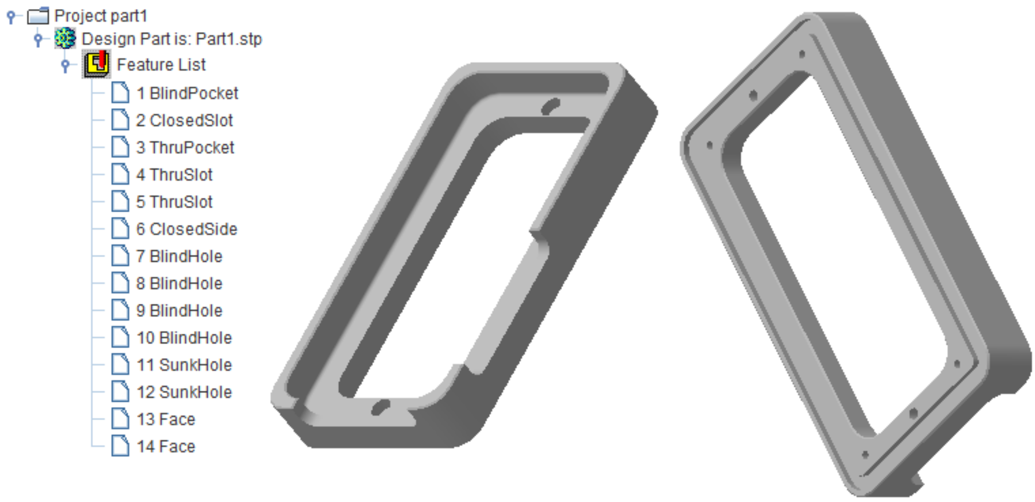
Unlike the optimization stage of the process parameters in Section 4.3, the Pattern Search method is not suitable for this type of problem as all the variables need to be optimized are discrete values. The performances of the Genetic Algorithm and Simulated Annealing algorithm are then compared and the Simulated Annealing algorithm is proven to be more reliable in finding the global optimum. As thus, the Simulated Annealing algorithm is employed here.

The geometric and manufacturing interactions between machining features/operations as well as the technological requirements in parts are considered to generate some precedence constraints between the machining features/operations. The definitions and classifications of precedence constraints between machining features/operations can be found in (Li et al., 2006). A penalty function for handling the precedence constraints is used in the optimization process.

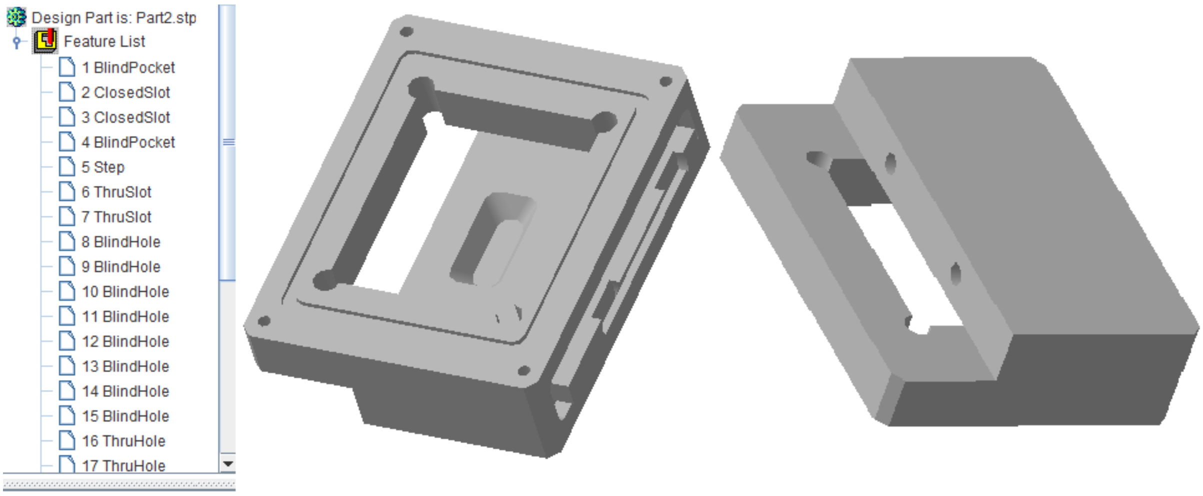
6. Case Studies

Two parts shown in Figure 6, provided by a Medium-size manufacturing company from an EU sponsored CAPP-4-SMEs project consortium (http://www.capp-4-smes.eu/), have been used to validate the developed approach. Both parts are imported as STEP files and a developed machining feature recognition processor has been applied to extract machining features (Li et al., 2006). The relevant specifications of the features in each part are listed in Table 4 and Table 5 respectively. The assumptions for process planning and scheduling include:

- Parts are independent, and part preemption is not allowed;
- A penalty function is applied to the optimization process to ensure that the sequence of the operations generated for each part complies with precedence constraints;
- All parts and machines are available at time zero simultaneously;
- Each operation can be performed on multiple machines, and each machine can only execute an operation each time;
- Machines are continuously available for production;
- If a machine is broken down, or a new part is inserted, the algorithm can re-start and generate new process plans and a schedule efficiently;
- The time for a set-up is assumed to be identical and independent of specific operations. For the milling operations on each machine, the cutter will be kept the same. From a milling operation to a drilling operation, a tool change will be made. The time for a machine change or a tool change are also assumed to be identical and independent of specific operations;
- This research is only for milling process parameter optimization at this moment. For the drilling features/operations in the parts, the energy consumption for the drilling process of each feature/operation is estimated and proportional to the volume of the feature.



(a) Part 1 and its recognized machining features



(b) Part 2 and its recognized machining features

Figure 6: Feature lists of test parts with Part 1 having 14 features and Part 2 having 29 features.

Table 4: The specifications of feature operations in Part 1.

Features	**Volume(mm^3)**
1- BlindPocket	70,800
2-ClosedSlot	1,360
3 –ThruPocket	3,590
4-ThruSlot	1,536
5- ThruSlot	1,408
6- ClosedSide	6,984
7/8/9/10 -BlindHole	28.5
11/12-SunkHole	154.3
13-Face	8,375
14-Face	8,375

Table 5: The specifications of feature operations in Part 2.

Features	**Volume(mm^3)**
1- BlindPocket	798
2-ClosedSlot	420
3- ClosedSlot	2,190
4 -BlindPocket	16,200
5-Step	15,000
6/7- ThruSlot	86.6
8/9- BlindHole	67
10/11/12/13 -BlindHole	23.75
14/15/-BlindHole	196.25
16/17-ThruHole	196.25
18/19/20/21/22-Face	2,850/1,080/4,350/710/2,850
23/24/28-Face	300/219.5/986
25/26/27/29-Face	40

Three CNC machines have been used as the candidate machines for this research validation. The first machine is the Hurco vertical machine center used in (Yan and Li, 2013), and other machines are two Haas vertical machine centers VF-4 and VF-7.

6.1 Monitoring system deployment

A wireless sensor network system for monitoring three-phase electricity consumption and a Cloud-enabled data server to record and share data over the Internet have been developed and deployed in a shop floor. Energy information measured from machines and transmitted as IPv6 packets to the data server using a wireless transport protocol 6LoWPAN. The sample rate of energy measurement is at 100 samples per second. The above system is illustrated in Figure 7. The hardware photos and software interfaces are shown in Figure 8. Surface roughness is measured off-line.

6.2 Optimization of milling process parameters

As described in Section 4.1, in order to optimize the milling parameters, ANNs are constructed to represent the relationships between the key milling parameters (n, c, a_p, a_e) and the measured Surface roughness S, and between (n, c, a_p, a_e) and measured Energy consumption E. To save space, only the measured data set from the Hurco vertical machine center is used here to illustrate the optimization procedure of milling process parameters. The lower and upper bounds and intervals of the milling parameters set for optimization are shown in Table 6. To train the ANNs properly, the measured dataset is divided into three groups: 4 data as validation dataset, 4 data as test dataset and the remaining 19 data as test dataset. 3-layer ANNs with 6 hidden neurons are constructed to approximate the measured energy consumption as is shown in Figure 9. The mean Squared Root Error between the measured and predicted energy consumption values is 1.39 KJs, and the maximum error in percentage is 9.82% which occurs in the test set. Similarly, 3-layer ANNs with 10 hidden neurons are employed to represent the Surface roughness. The comparison of the predicted and measured Surface roughness is depicted in Figure 10, with a mean squared root error of 0.018 μm and a maximum error of 6.85%.

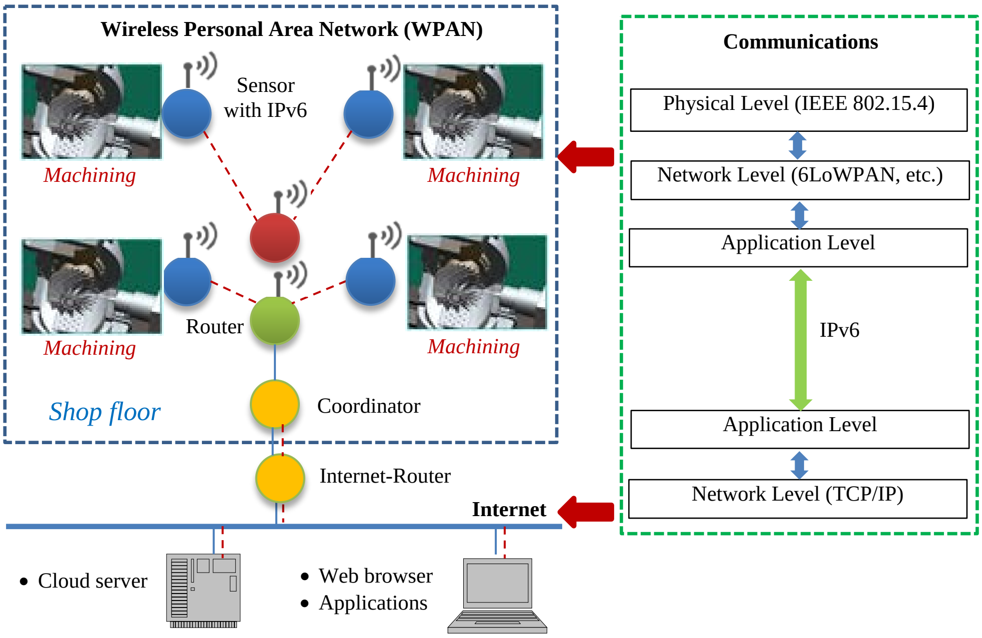
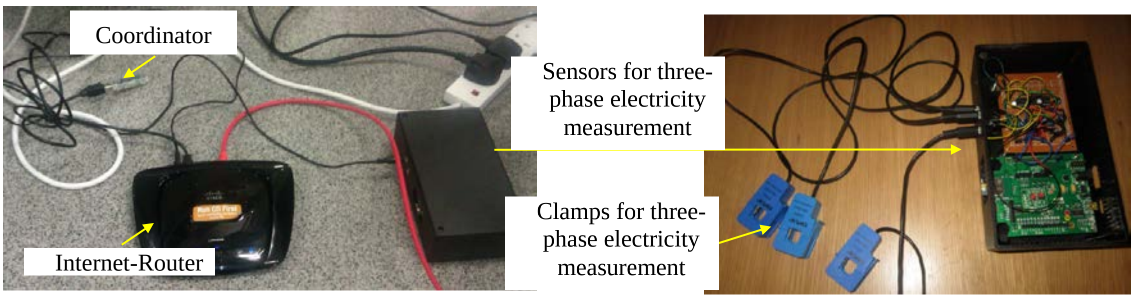
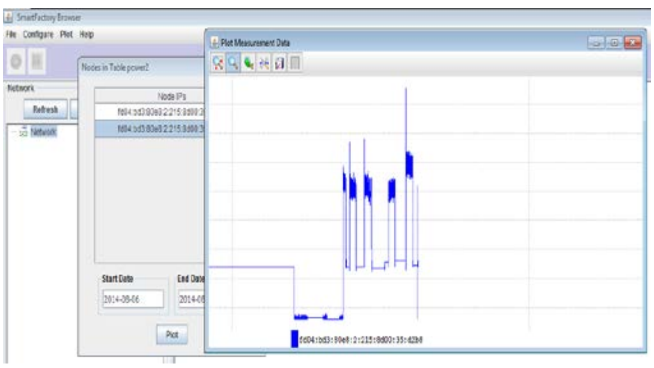


Figure 7: The deployment diagram of the energy monitoring system.



(a) Wireless sense network-based three-phase electricity consumption measurement system



(b) Measured electricity consumption stored in Cloud server

(c) Surface roughness tester (off-line measurement)

Figure 8: The energy monitoring system and surface roughness testing.

Table 6: The bounds of the milling parameters for optimization.

Milling parameters	n **(r/min)**	c **(mm/min)**	a_p **(mm)**	a_e **(mm)**
Lower bound	1000	200	0.2	5
Upper bound	2000	300	0.4	15
Interval	500	50	0.1	5

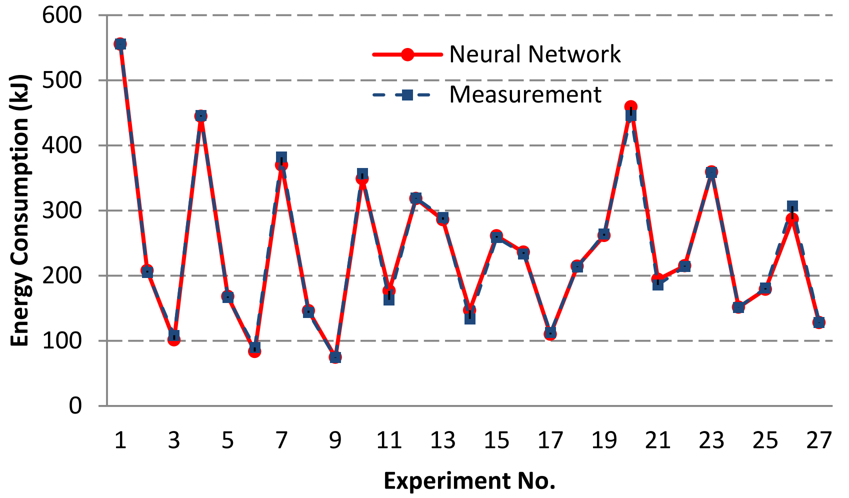


Figure 9: Comparison of the measured and ANNs-predicted energy consumption.

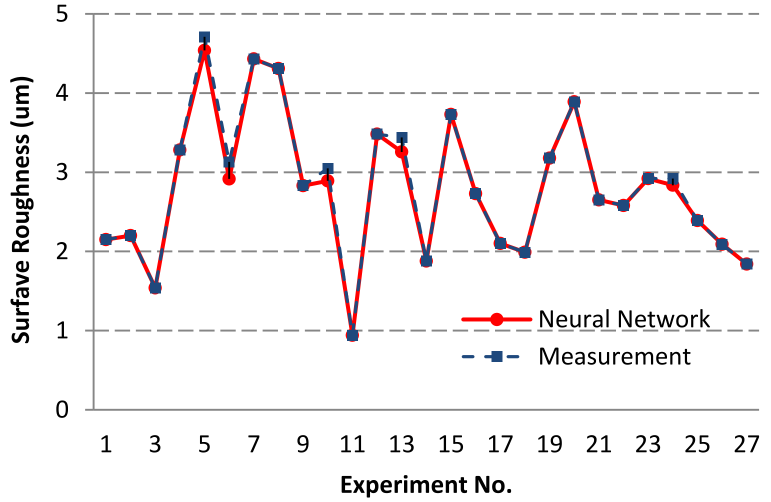


Figure 10: Comparison of the measured and ANNs-predicted surface roughness.

The ANNs-predicted energy consumption and calculated *MRR* are then pre-processed into grey relational coefficients to form the sum-weighted objective function for optimization. The constraint on surface roughness is accounted into the objective function as a penalty function when the ANNs-predicted surface roughness is greater than the value of the user defined surface roughness.

Three optimization algorithms, i.e., Pattern Search, Genetic Algorithm and Simulated Annealing algorithm, have been tested with the requirement of Surface roughness S set at 2.5μm. The optimization processes and results are shown in Figure 11 and Table 7. It is observed that Pattern Search is the most stable and efficient among the three algorithms.

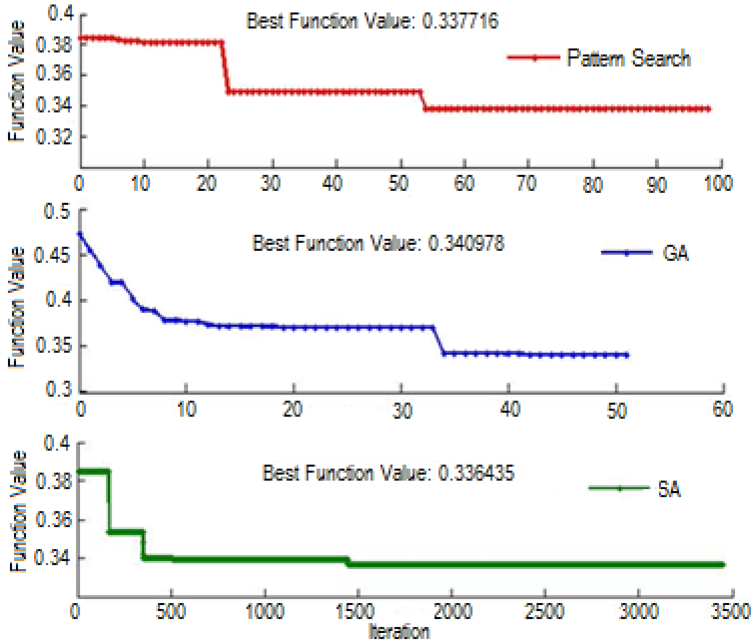


Figure 11: Comparison of three optimization processes.

Table 7: Result comparison of the three optimization algorithms.

Algorithms	**Average time (*s*)**	**Best solutions (3 trials with S ≤2.5 *μm*)**		
Pattern Search	9.23	0.3377	0.3377	0.3377
Genetic Algorithm	24.25	0.3376	0.3406	0.3410
Simulated Annealing	152.84	0.3364	0.3392	0.3409

Surface roughness is not considered as an optimization objective directly in this work. Instead it is used as a constraint which can provide the flexibility to users to set the desirable surface roughness depending upon the process requirement of roughing, semi-finish and finish during process planning. As thus, the optimized results of process parameters will be different according to the various requirements of surface roughness in process planning. The intermediate processes and optimized results for three roughness requirements are illustrated in Figure 12 and Table 8. As expected, the greater energy consumption and the lower *MRR* are needed when the requirement on surface roughness is tighter (with a lower value of surface roughness).

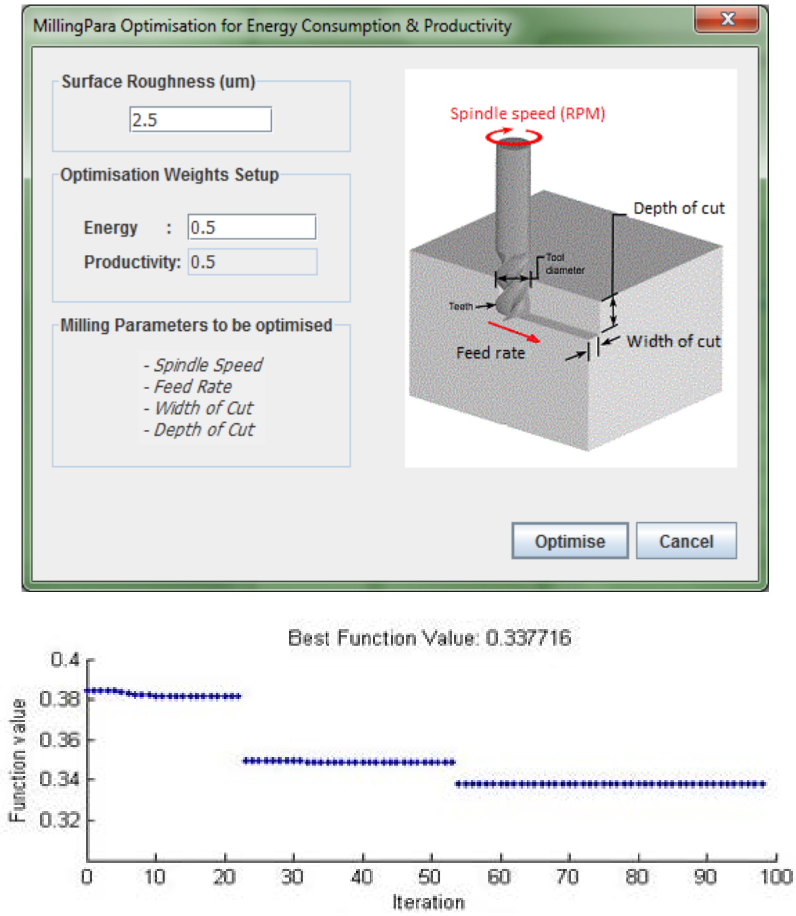


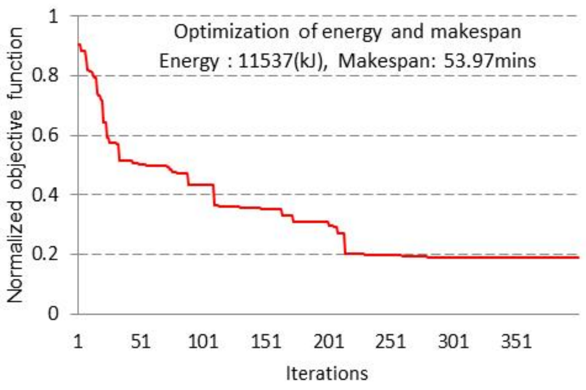
Figure 12: Intermediate results of Pattern Search.

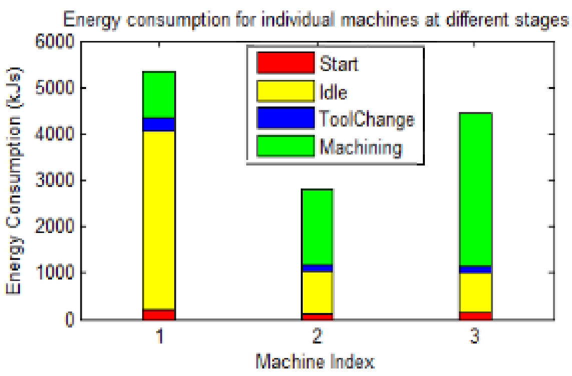
Table 8: Optimized process parameters for different constraints on surface roughness.

R_a(μm)	n (r/min)	c (mm/min)	a_p (mm)	a_e (mm)	MRR (mm^3)	E (kJ)
2.5	1103.0	300.0	0.3938	15.0	1771.9	84.276
2.0	1000.0	205.64	0.4000	15.0	1234.0	105.690
1.5	1113.5	200.0	0.3938	15.0	1181.3	116.180

6.3 Optimization of process sequencing, setting-up and scheduling

The optimized milling parameters of individual machines according to the roughness requirement are then recorded and the optimized *MRR* and energy consumption for individual machines are fed into the optimization of process planning and scheduling as inputs. The machining times of individual features/operations on various machines are calculated using the optimized *MRR*. The working *SEC* for individual machines can be obtained using the optimized energy consumption. As mentioned in Section 5.3, the most suitable optimization method for this application is the Simulated Annealing algorithm, thus optimization results using the algorithm are shown in Figures 13 - 15. The optimization progress for energy consumption and makespan is shown in Figure 13(a) and the energy consumption at different stages of machining and on different machining features/operations is shown in Figure 13(b) and Figure 14 respectively. The optimization results only for energy consumption are shown in Figure 15. For the optimization of energy consumption and makespan, the total energy consumption is 11537 KJs, makespan is 53.97 minutes and all machines are involved in the jobs; On the contrast, for the optimization of energy consumption only, the total energy consumption is reduced to 8742 KJs while makespan is increased to 76.4 minutes and the 1st machine is not be scheduled due to its high *SEC* and idle consumption compared to the other two machines. The optimization algorithm can also address the dynamics of process planning and scheduling. Table 9 shows the results with different selections of machines and optimization objectives. Compared with the results for the two optimization objectives, there is always a tradeoff between the energy consumption and makespan when scheduling multiple operations over multiple machines. The optimal energy consumption is achieved when makespan is not taken into account. By the comparison of the results with different combinations of machines, it is noted that the more selections of machines will always ensure a shorter makespan, but not necessarily lead to less energy consumption.





(a) Optimization process (b) Energy consumption at different stages

Figure 13: Optimization of machine systems in terms of energy consumption/makespan.

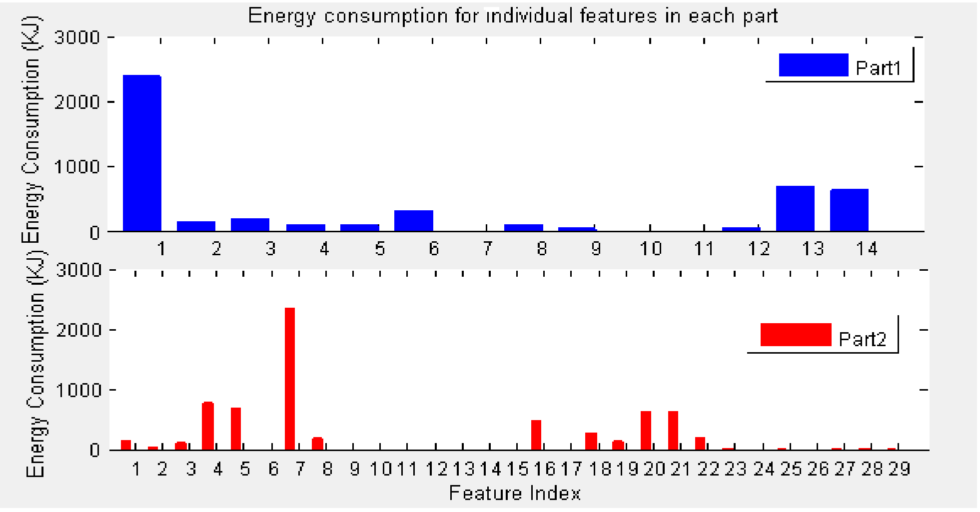
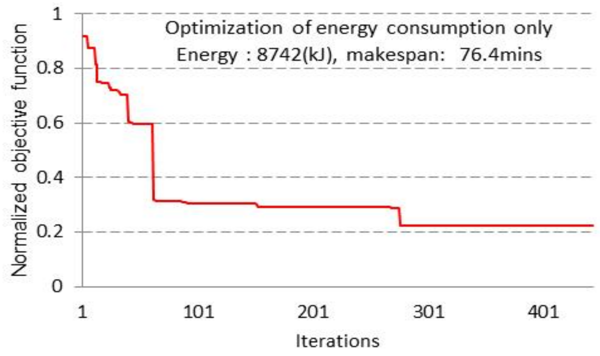
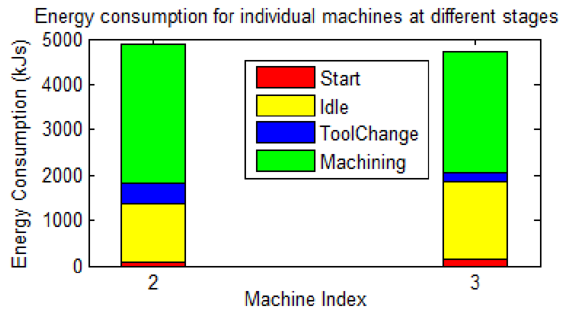


Figure 14: Energy consumption for machining features of the two parts.



(a) Optimization of process planning and scheduling



(b) Energy consumption at different stages

Figure 15: Optimization of process planning and scheduling in terms of energy consumption.

Table 9: Optimization results under different conditions and objectives.

Optimization objective	Available machines	Energy (KJs)	Makespan (minutes)
Energy&Makespan	All	11537	53.97
	2&3	11376	67.59
	1&3	12368	65.43
	1&2	12497	66.84
Energy	All	8742	76.40
	2&3	8742	76.40
	1&3	9453	75.58
	1&2	10012	78.36

7. Conclusions

It is critical for companies to develop and deploy process planning and scheduling optimization adaptive to dynamics inherent in modern machining processes in order to implement manufacturing sustainability in terms of energy consumption, product quality and productivity. This research presents a systematic approach for sustainable process planning and scheduling optimization with built-in intelligent mechanisms for better adaptability and responsiveness to manufacturing dynamics. Multiple criteria such as energy consumption, surface quality, productivity and makespan are considered concurrently to realize constraint-based multi-objective optimization. In the approach, ANNs are used to leverage the robustness and extensibility characteristics to a large amount of measured process data to establish the complex non-linear relationships between key process parameters and multiple objectives. Intelligent algorithms, including Pattern Search, Genetic Algorithm and Simulated Annealing algorithm, are applied and benchmarked to identify optimized solutions. The developed approach, verified through industrial case studies, shows significant application potential.

The contributions of the approach are summarized below:

- A systematic, adaptive and efficient approach has been developed to address the different levels of a dynamic machining shop floor to meet the multiple performance criteria such as sustainability, productivity, surface quality and makespan. The models developed in this research are extensible to include more performance criteria to address companies' specific requirements;

- Investigations on the characteristics of energy consumption influenced by key process parameters, machining feature/operation-based process plan, and schedules on machine systems. Intelligent and robust decision making processes for process planning and scheduling have been effectively developed. The above work paves a way for the approach to be integrated into modern feature-based CAM systems to facilitate the sustainable management of shop floors in companies.

Further investigations and improvements of the research are ongoing, mainly from the following aspects:

- In a shop floor, air conditioning, ventilation and compressed air equipment and related networks, could consume energy significantly. The issue will be investigated in the future research;
- Machining operations deduced from machining features need to be further refined to support the sustainability decision making in more detail;
- Full-scale industrial pilot runs of the system in machining companies in UK, Sweden, Spain and Germany for demonstration to the entire European industries are under preparation according to the arrangements of the projects.

Acknowledgement

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