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Cyber Physical System and Big Data Enabled Energy Efficient Machining Optimisation

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Abstract

Due to increasingly customised manufacturing, unpredictable ambient working conditions in shop floors and stricter requirements on sustainability, it is challenging to achieve energy efficient optimisation for machining processes. This paper presents a novel Cyber Physical System (CPS) and Big Data enabled machining optimisation system to address the above challenge. The innovations and characteristics of the system include the following four aspects: (1) a novel process of "scheduling, monitoring/learning, rescheduling" is designed to enhance system adaptability during manufacturing lifecycles; (2) an innovative energy model to support energy efficient optimisation over manufacturing lifecycles is developed. The energy model, which is enabled by CPS, Big Data analytics and intelligent learning algorithms, considers dynamic and aging conditions of machine tool systems during manufacturing lifecycles; (3) an effective evolutional algorithm based on Fruit Fly Optimisation (FFO), is applied to generate an adaptive energy efficient schedule, and improve schedule when there are significantly varying working conditions and adjustments on the schedule are necessary (that is rescheduling); (4) the system has been successfully deployed into European machining companies to verify capabilities. According to the results, around 40% energy saving and 30% productivity improvement have been achieved in the companies. A practical case study presented in this paper demonstrates the effectiveness and great potential of applicability of the system in practice.

Keywords: Cyber Physical System, Big Data, Energy efficient machining, Scheduling optimisation

1. Introduction

Manufacturing such as Computer Numerical Control (CNC) machining is characterised by increasingly customised and low-volume orders as well as stricter energy saving and faster delivery requirements for products. That is, in a manufacturing shop floor, there could be various changes on order priorities, unexpected delays and ambient working conditions, requiring companies to rapidly adjust their manufacturing processes timely to fit the current conditions. Meanwhile, manufacturing processes are energy intensive due to the powering and heating of motors, compressors and machine tool systems, making the manufacturing sector one of the primary energy consumption sources. Accordingly, in recent years, energy efficiency related regulations and incentives have taken effect to drive the manufacturing industry undergoing a full-scale transformation towards sustainability (Stark et al., 2017). In manufacturing, scheduling is a key enabler to improve manufacturing sustainability and enhance shop floor performance (Li and McMahon, 2007; Wang et al. 2015). On the other hand, the developed scheduling systems are mainly based on pre-defined conditions of machine tool systems for decision-making and optimisation. The conditions are presumed to be unchanged during machining lifecycles. However, machine tool systems are prone to aging and degrading, resulting in dynamic breakdowns and adjustment requirements during manufacturing lifecycles. This issue has not been addressed in the scheduling research yet, which cripples the effectiveness of energy efficient scheduling in supporting manufacturing sustainability.

In this paper, an innovative energy efficient machining system (I^2S) has been developed. Enabled by CPS, Big Data analytics, intelligent learning and optimisation algorithms, Due to integration of these technologies, the proposed I^2S can be effectively adapted to dynamic machining conditions while achieving the energy efficient requirement. CNC machining processes have been selected for system development, validation and industrial deployment. The innovations and characteristics of the research are below:

- A novel process of "scheduling, monitoring/learning, rescheduling" during machining lifecycles has been developed. That is,
    - Based on historical energy consumption data from previous manufacturing cycles, an effective Fruit Fly Optimisation (FFO) algorithm is applied to achieve multi-objective optimisation as an initial schedule;
    - During the manufacturing lifecycle, CPS is used to continuously monitor the energy consumption patterns of components' machining, meanwhile the monitored data are analysed by using Big Data Analytics algorithms to predict the conditions of machine tool systems. Based on these two processes, an updated rescheduled plan will be generated by using the FFO algorithm when there are significantly varying conditions occurred and adjustments on scheduling are needed.
- The proposed I^2S is innovative in that the aging conditions of machines and cutting tools are considered in an innovative energy model during a manufacturing lifecycle. This will establish a more accurate energy model thereby achieving effective scheduling. Meanwhile, based on this process, prior experiments, required to establish the energy models of machine tool systems for scheduling optimisation, are minimised, thereby improving the efficiency and effectiveness of scheduling.
- CPS, Big Data analytics, intelligent learning and optimisation algorithms are integrated for systematic implementation of manufacturing intelligence. Benchmarking and analysis are

conducted to justify the methodologies and intelligent mechanisms. The system has been validated through various real-world industrial case studies in European machining companies. The successful industrial deployment and validations demonstrate the effectiveness and significant potential applicability of I^2S in practice.

The rest of the paper is organised as follows: In Section 2, literature surveys on energy modelling and machining scheduling optimisation, CPS and Big Data technologies for intelligent manufacturing systems are given. In Section 3, the system functions and framework are presented. In Section 4, algorithm designs of Artificial Neural Networks (ANN)-based energy modelling and monitoring are discussed in detail. The scheduling/rescheduling optimisation is described in Section 5. The CPS infrastructure, case studies and system validation are given in Section 6. In Section 7, conclusions are drawn and future research directions are outlined.

2. Literature Survey

In the past decade, attributing to the increasing importance on sustainable manufacturing, research on energy efficient scheduling has been actively conducted. The relevant research has been mainly investigated from two aspects: 1) energy modelling to support scheduling, and 2) effective algorithms and strategies to optimise energy efficient scheduling. Meanwhile, due to the development of IT technologies, research on CPS and Big Data for manufacturing has been conducted in recent years. Comprehensive review and research frameworks can be found from Wang et al. (2015), Gahm et al. (2016) and Babiceanu and Seker (2016). The latest research is summarised below.

2.1 Energy modelling for manufacturing

Sustainability and energy saving are important aspects to be considered in manufacturing optimisation nowadays. It is essential to build effective energy models to support sustainability optimisation. Fang et al. (2011) developed a generic multi-objective mixed integer programming formulation. An energy model has been established based on an empirical machining model. The model considers width of cut, feed per tooth, machining speed and specific machining energy. He et al. (2011) built an energy assessment framework for a machining workshop based on CNC codes. The framework consists of four layers, i.e., workshop layer, task layer, manufacturing unit layer and machine tool layer. For each layer, the major element that affects the energy consumption mostly is modelled. Yan and Li (2013) proposed a thermal equilibrium and empirical approach for energy consumption modelling during machining processes. The model includes various machining parameters, such as material removal rate, idling power, machine tool specific coefficients and standby power etc. Winter et al. (2014) developed a sensitivity analysis method to analyse the energy performance of a grinding process, in which energy consumption is affected by key grinding parameters, including grinding depth, grinding speed and dressing speed. Wang et al. (2015) built multi-level models for energy consumption from two levels: 1) on a machining level, ANNs are employed to estimate energy consumption and surface roughness based on the spindle speed, machining speed, depth of cut and width of cut; 2) on a shop floor level, an energy model is established, in which start-up, idle, machining and shutdown phases are considered. Yan et al. (2016) designed a multi-level model to optimise energy consumption from both machining parameters and shop floor levels. It requires off-line experiments to build the energy model of machining processes based on qualitative analysis and grey relational analysis. A model in a shop floor consists of processing energy, set-up energy, transportation energy, standby energy, and overhead energy. The above works are summarised in Table 1.

However, in the above work, the dynamic conditions of machine tool systems (e.g., aging and wear conditions of machines and cutting tools) have not been considered in energy modelling, which highly limits adopting the models to be used in a real production line due to the low accuracy in a complex and unpredictable environment. Meanwhile, in the past research, energy modelling is established via experiments before production. It could be highly beneficial if energy models could be developed and timely updated along with manufacturing lifecycles by avoiding gruelling and time-consuming experiments.

Table 1: Energy models for machining processes.

Works	**Input**	**Optimisation targets**	**Research methods**
Fang et al. (2011)	Machining width, feed per tooth, machining speed and specific machining energy	Makespan, peak power demand, and carbon footprint	Empirical models and case studies of machining cast iron plates with slots
He et al. (2012)	CNC codes	Energy consumption for spindle, axis feed, tool changes, coolant pump and fixed energy consuming units of CNC machines	Empirical models for spindle, axis feed, tool changes, coolant pump and fixed energy consuming units
Yan and Li (2013)	Material removal rate, idle power, machine tool specific coefficients and standby power	Energy consumption model	Thermal equilibrium and empirical
Winter et al. (2014)	Machining depth, machining speed and dressing speed	Energy consumption	Sensitivity analysis method
Wang et al. (2015)	Spindle speed, machining speed, depth of cut and width of cut	Surface quality, energy consumption and machining removal rate	ANNs to establish a model for surface quality and energy consumption
	Number of machines and the number of jobs to be processed	Energy consumption for idle, working, tool change and set-up	Empirical models for idle, working, tool change and set-up

Yan et al. (2016)	Material removal rate, spindle speed Number of machines and the number of jobs to be processed	Idle power and operation power, energy consumption for processing set-up, transportation, standby, and overhead	Off-line experiments for grey relational analysis Empirical models for processing, set-up, transportation, standby, etc.

2.2 Energy efficient scheduling for manufacturing

Based on energy models, optimisation algorithms are applied to improve the energy efficiency of machining processes. A number of research works have focused on investigation of better optimisation algorithms to improve the energy efficiency of machining processes. Tang et al. (2016) developed an improved Particle Swarm Optimisation (PSO) approach to address dynamic scheduling under unexpected disruptions, so energy consumption and makespan can be reduced simultaneously. Liu et al. (2016) developed a novel multi-objective Genetic Algorithm (GA) based on NSGA-II to minimise the total non-processing electricity consumption and total tardiness. The process provides a function for parent and children combination as well as elitism to improve the optimisation efficiency. Yan et al. (2016) designed a multi-level energy model, utilised grey relational analysis to optimise machining parameters and applied a Genetic Algorithm to optimise the makespan and energy consumption. Xu et al. (2016) designed an enhanced Pareto-based bees algorithm to optimise energy consumption and productivity. Salido et al. (2016) developed a memetic algorithm to minimise energy consumption under makespan constraints within a reschedule zone. The above works are summarised in Table 2.

On the other hand, dynamics and varying ambient working conditions in shop floors could lead to unexpected breaks and unnecessary inspection, standby, repairing and maintenance of manufacturing systems, thus resulting in waste of time, energy and resource (Wang et al., 2015). It is imperative to incorporate CPS-based condition monitoring and Big Data analytics into scheduling optimisation so that the system will be able to respond to rapid the changing working conditions efficiently during manufacturing lifecycles.

Table 2: Optimisation algorithms of energy efficient scheduling for machining.

Works	**Optimisation targets**	**Algorithms**
Tang et al. (2016)	Energy consumption and makespan	Improved particle swarm algorithm
Liu et al. (2016)	Energy consumption and tardiness	NSGA-II based genetic algorithm
Yan et al. (2016)	Makespan and energy consumption	Grey relational analysis, genetic algorithm
Xu et al. (2016)	Energy consumption and productivity	Enhanced Pareto-based bee algorithm
Salido et al. (2016)	Energy consumption	A memetic algorithm

2.3 CPS and Big Data technologies for manufacturing

With more and more widespread CPS in a manufacturing sector, Big Data technologies has been increasingly considered as a leverage for industries to streamline manufacturing management. Nagorny et al. (2012) developed CPS to support control, monitoring and management for manufacturing devices in a manufacturing shop floor. Big Data technologies for the Engine Health Monitoring Unit (EHMU) were developed in Rolls-Royce Plc. to monitor and optimise system performance and manufacturing quality by collecting real-time Big Data from working engines, systems and factory lines. In Raytheon Corp, a Big Data technology was implemented in a smart factory to manage information from different data sources, such as sensors, simulations and all other manufacturing records in the factory (Noor, 2013). Prabhu (2013) investigated Big Data collection using CPS. The collected data can be modelled as a set (device ID, time, event ID) to support real time device monitoring and response by actuators. Chaplin et al. (2015) developed a method for the integration of legacy CNC controllers and decentralisation, context-awareness, and data distribution services. Liu and Jiang (2016) designed CPS for intelligent manufacturing with Big Data collection, processing and visualisation. The system was validated in a micro manufacturing system lab. The above works are summarised in Table 3. When Big Data are accumulated, effective information management infrastructures, such as Hadoop Distributed File System (HDFS), MapReduce, YARN, HBase, HiveQL and NoSQL, become effective tools for storing, managing, processing, interpreting, and visualising of Big Data (Loshin, 2014). Thus, Big Data analytics are imperative to facilitate intelligent decision marking and optimisation in manufacturing.

Table 3: CPS and Big Data technologies for manufacturing applications.

Works	System characteristics
Dai et al. (2011)	Integrating Big Data platform in cloud for dataflow-based analysis
Nagorny et al. (2012)	CPS devices, information collection for reasoning-based control, monitoring, and management functions.
BigData-Startups (2013)	Big Data for Engine Health Monitoring Unit
Noor, A. (2013)	Big Data technology to achieve smart factories to manage information from different data sources
Prabhu (2013)	CPS as a set model with device ID, time, event ID, which can be modified
Chaplin et al. (2015)	Integration of legacy CNC controllers with decentralisation, context-awareness, data distribution services
Liu and Jiang (2016)	CPS for achieving intelligent manufacturing establishment for Big Data collection, processing and visualisation

In summary, based on aforementioned research works, the following research gaps and requirements are identified:

- The current researches on optimisation of energy efficient scheduling are mainly relying on prior/off-line experiments to develop energy models. This highly time consumed and heavily labour engaged low effort method is not fitted for supporting dynamic industrial cases. Future research should ensure energy models to be established and timely updated throughout manufacturing lifecycles to improve the efficiency and effectiveness of the energy modelling;

- It is critical to develop an adaptive CPS and Big Data enabled system to efficiently optimise multi-objective schedules for highly customised manufacturing. Through this system, the complex and rapid changing conditions during customised manufacturing lifecycles can be effectively captured and corresponding optimisation solution can be developed to achieve the best system performance during machining lifecycles;
- It is very rare to have an industry implementation to validate the proposed system in a real-world case to prove the system capabilities. It will be a significant contribution if the developed systems are proved through system deployment in factories by using various industrial real-world case studies for system validation.

3. System Functions and Framework

3.1 System functions

As reviewed earlier, scheduling for CNC machining processes in a shop floor has been developed based on pre-defined machining conditions. Generated scheduling plans are represented in a relatively rigid format (Zhou et al., 2009). On the other hand, machining in shop floors has become increasingly customised. Machining customisation is characterised by upcoming disturbance, disruption and uncertainty (e.g., dynamic changes of job priority, unexpected delay, aging or degrading of tooling and machines, etc.) (Adibi et al., 2010). It is essential to update scheduling flexibly when machining conditions are changed in a shop floor to ensure the effectiveness of optimised schedules. It is critical to have real-time monitoring, analysis and optimisation functions to address specific and dynamic working conditions for achieving adaptive scheduling optimisation. The current practice of the relevant data collection in shop floors is mainly based on manual processes. Due to large quantities and diverse product models, this data collection process is tedious and error-prone. To address the challenge, in this research, a novel I^2S (CPS and Big Data enabled machining scheduling optimisation system) has been developed. I^2S, which is shown in Figure 1, consists of the following functions:

- A wireless sensor network has been designed and integrated with CNC machines as CPS for measuring the energy consumption of CNC machines to support scheduling optimisation. Electricity measurement sensors are mounted onto CNC machines for electricity energy collection;
- A Big Data infrastructure has been developed for collecting, storing, processing and visualising real-time energy data from the wireless sensor network which is integrated into the CNC machines;
- Scheduling and rescheduling functions have been developed into the system. For scheduling, an ANN-based algorithm (i.e., energy modelling-ANN) has been designed to establish the energy models of components machined in a shop floor. Based on these energy models, a scheduling

optimisation algorithm would generate an optimal schedule with the target of minimal energy consumption, the shortest makespan and the most balanced level of utilisation. When the difference between the predicted energy model and real energy model is large, the energy model will be updated and rescheduling optimisation process will be triggered. Furthermore, in order to accurately indicate the abnormal machining condition from dynamic environments, another ANN-based algorithm (i.e., energy monitoring-ANN) has been developed to identify the energy patterns of machining components under the current working conditions. Rescheduling optimisation process will be triggered using the scheduling algorithm to obtain an updated scheduling plan when significant difference of energy patterns is identified, which may indicate machine problem/tool wear/new orders requiring rescheduling adjustments. More details of the above processes are explained in the following sections.

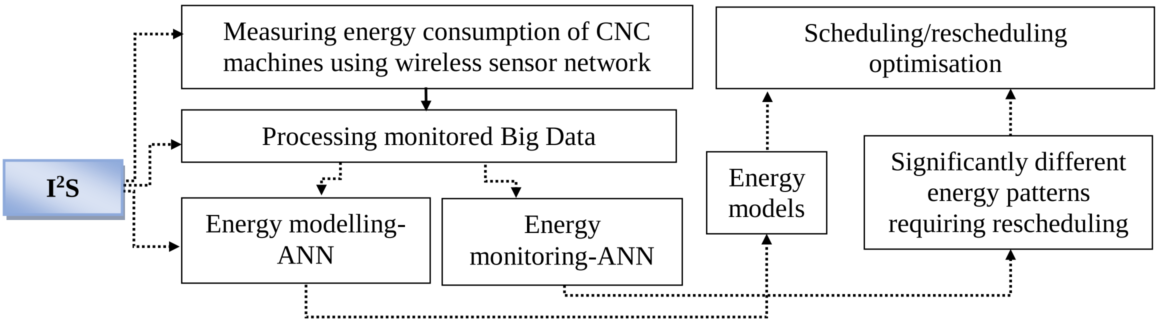


Figure 1: Functions of I^{2}S.

3.2 System flow

I^{2}S adopts a novel process of “scheduling, monitoring/learning, and rescheduling” for manufacturing lifecycles. The detailed process is shown in Figure 2. Explanations are given below:

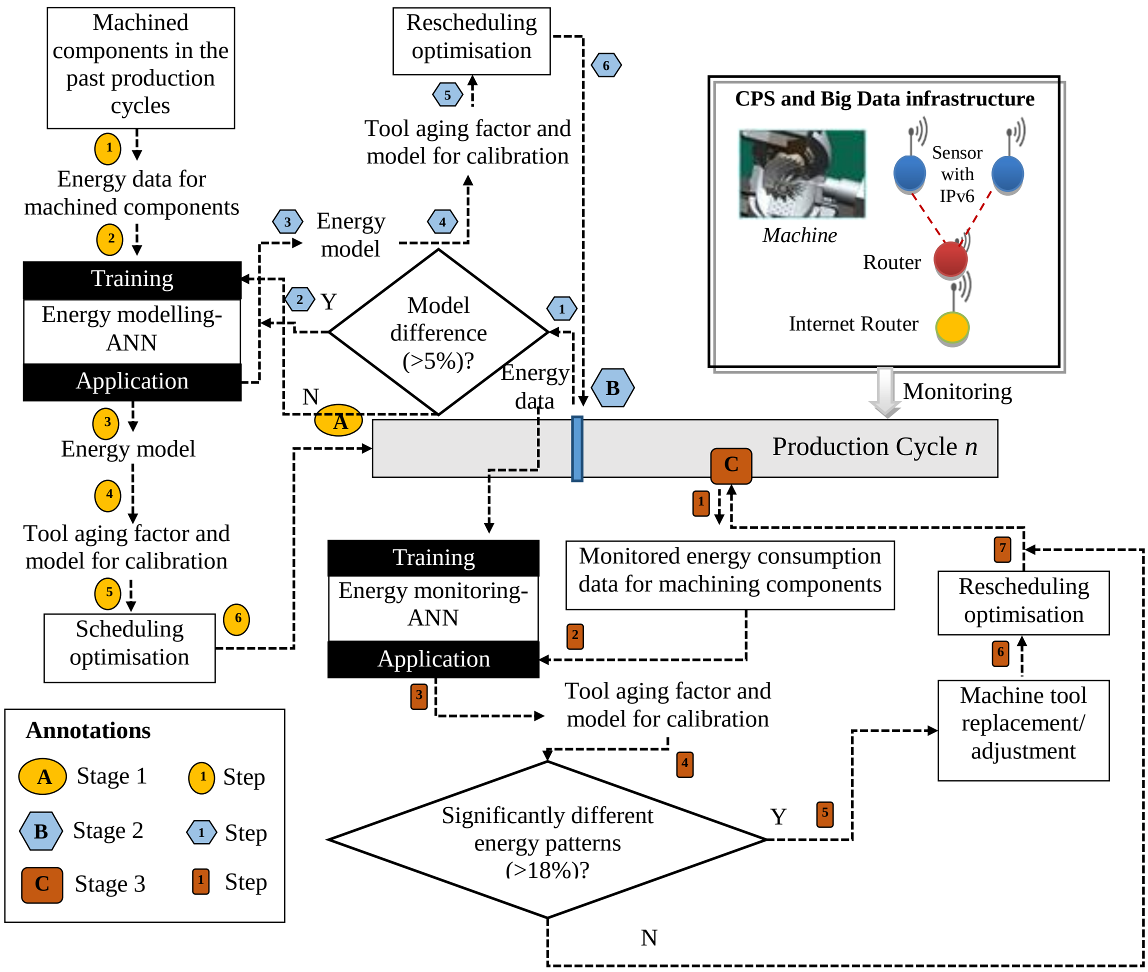


Figure 2: I^{2}S for scheduling, monitoring/learning and rescheduling.

- Normally, a customised machining process can be managed as a series of production cycles in a shop floor. During a production cycle, the types and quantities of components for production are certain. When a new production cycle starts, the types of components could be updated to the system. New types may be added and old types during the last production cycle may be discontinued for further machining during this cycle. Scheduling optimisation needs to consider the dynamic characteristics of production cycles to achieve multi-objective optimisation, such as the least overall energy consumption for the production line, the shortest makespan, and the most balanced utilisation of machines, etc. During machining, CNC machines are continuously monitored via the WSN and the collected energy consumption data are stored in the Big Data infrastructure for further processing and analysis;
- A production cycle is defined as three stages. These stages are described below:
  (1) Stage A (start point of a production cycle): The energy modelling-ANN, which uses precision requirement, machining feature quantity, material and machining volume as inputs, will be trained and applied to estimate the energy consumptions (energy models) and machining time of new components. For the energy models, a tool aging factor and model are innovatively

used to adjust the models to accurately reflect the current situation. The energy models are prerequisite for schedule optimisation to generate an optimised schedule. The energy modelling-ANN has been trained based on the historical data for those components machined in previous production cycles. For new types of components added into this production cycle, their energy consumption can be estimated by using the energy modelling-ANN;

(2) Stage B (during the manufacturing lifecycle): During the whole period of the manufacturing lifecycle, the difference between the predicted results of energy models and real energy data will be calculated. If the value of the difference exceeds a certain value (e.g. 5% - the rational to decide the value is given in Section 5.3), the energy data for machined components will be used to update the training of the energy modelling-ANN and energy monitoring-ANN to improve the accuracy of the scheduling (rescheduling).

(3) Stage C (during the manufacturing lifecycle): During the whole period of the manufacturing lifecycle, another ANN, i.e., energy monitoring-ANN, is also trained based on the historical data for machining components. In order to accurately identify abnormal cutting conditions from massive data set, continuously monitored energy data (power) are partitioned into a series of energy patterns according to the machining duration of each component and formed as the input vector. The output is a vector representing the type of the component. The deviation between the current energy pattern and standard energy pattern of the corresponding component is calculated. If the difference is within a small range (e.g., 18%, determined by experiments in Section 4.2), the tooling condition is in reasonable aging or degrading conditions; otherwise the system will consider that severe aging or degrading conditions of machines/cutters are occurred. An indicator message will inform the engineer that machines/cutters should be replaced or maintained/temporarily excluded from scheduling. Under the circumstance, rescheduling optimisation will be triggered to generate a reschedule plan.

- Through this design, the experiments, for establishing the energy consumption model of components to support scheduling and rescheduling optimisation, can be carried out during machining processes. Hence the time and cost required for scheduling and rescheduling can be significantly reduced and dynamic working conditions can be effectively addressed.

4. Energy Modelling and Monitoring

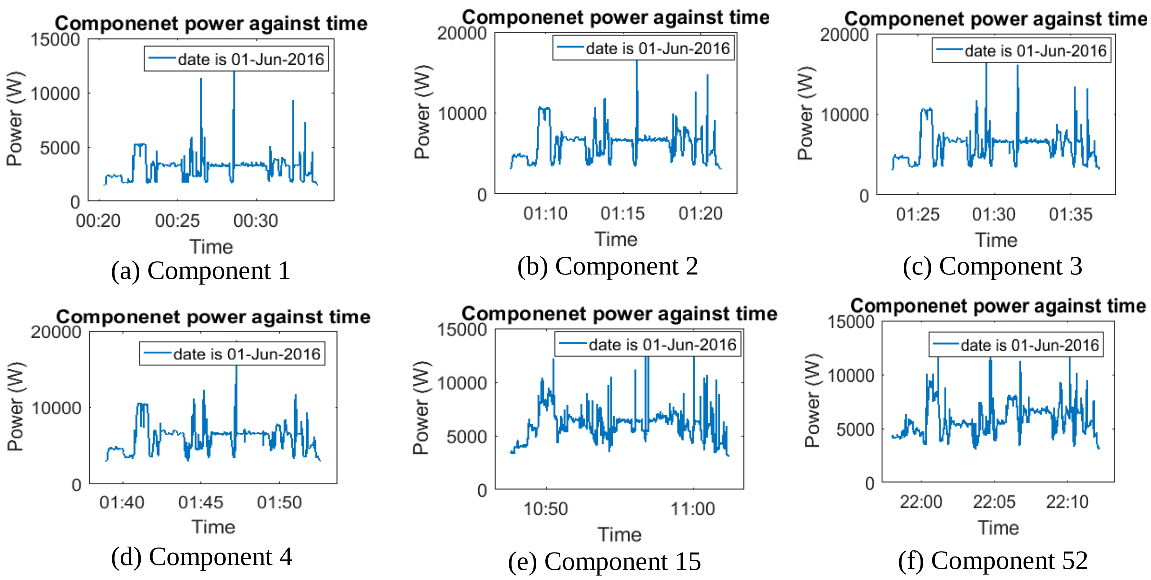
In I^2S, as shown in Figure 1 and Figure 2, the energy modelling-ANN has been designed to establish energy models for components machined in a shop floor. The energy modelling-ANN is used to predict the energy consumption for machining a component for scheduling and rescheduling optimisation. Meanwhile, the energy monitoring-ANN has been developed to monitor the machining process to identify abnormal conditions and support rescheduling if necessary. Design and analysis of the two ANNs are given below in detail. Meanwhile, the performance of the ANNs is compared with that of a latest deep learning algorithm for benchmarking analysis.

4.1 Energy modelling-ANN

The energy consumptions for machining two identical components under the different conditions of a cutting tool will be different. To support energy modelling, a tool aging factor and model will be first set up.

<u>Tool aging factor and model</u>

During the consecutive components machining, the machine tool will gradually wear during the metal cutting processes. This will lead deviation of energy consumption occurs even when the same component to be machined under the same tool and machining parameters. According to the research of Liu et al. (2016) and Sealy et al. (2016), the energy consumption could maximally increase for about 17% for using the same cutting tool to manufacture the same component within an acceptable surface quality range. Figure 3 shows an example of energy pattern changes from the identical component which have been consecutively machined 52 times by using single machine with the same settings.



(a) Component 1 (b) Component 2 (c) Component 3

(d) Component 4 (e) Component 15 (f) Component 52

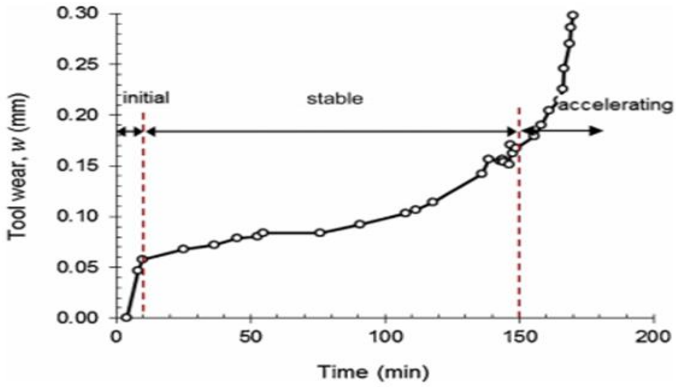
Figure 3: Energy pattern changes of 52 consecutive machining of identical components.

It can be observed that the energy consumption patterns gradually increase along the process of the machining lifecycle due to tool wear. Therefore, a tool aging factor is introduced to indicate the tool wear of a cutting tool for machining. It is presented in the following Equation 1:

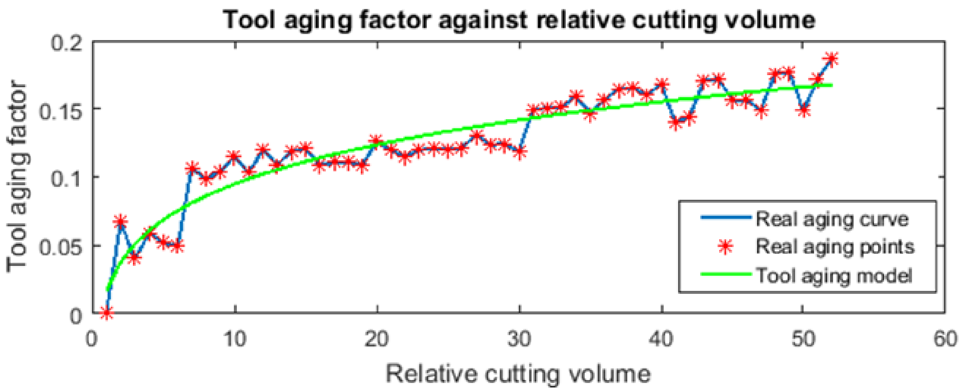
$$f(k) = \frac{E_k - E_{initial}}{E_{initial}} \times 100\% \tag{1}$$

where $f(k)$ is the tool aging factor of machining the k^{th} volume, E_k is the energy used for machining the k^{th} volume, and $E_{initial}$ is the energy consumed for machining the same volume using the cutting tool under its new condition.

The wear curve of a cutting tool is shown in Figure 4(a). The wear curve of a cutting tool consists of three regions: a break-in region, a steady-state region and a failure region. When the tool reaches the failure region, the quality of the machined component is low and the tool needs to be changed. Therefore, only the periods of break-in and steady-state are used during machining, and the tool aging factor is considered. Figure 4(b) shows that the tool aging process against the machined volumes from 52 cutting samples. The curves are aligned (without including the failure region).



(a) The wear curve of a cutting tool (Liu et al. 2016).



(b) The tool aging process against the machine volume.

Figure 4: Wear curve of a cutting tool and tool aging factor.

Based on the tool aging factor, a tool aging model can be established in the following Equation (2). A power curve fitting method is used based on the characteristics of factor distribution to build up the equation (Guest 1961).

$$T(k) = \beta_1 \times k^{\beta_2} + \beta_3 \tag{2}$$

where $T(k)$ is the predicted tool aging factor by regression computation for the k^{th} volume; β_1, β_2 and β_3 are the coefficients of the power curve.

The values of β_1-β_3 are decided by minimising the Root Mean Square Error (RMSE) between the tool aging factors $f(k)$ and the tool aging model $T(k)$. RMSE is defined in the following Equation:

$$RMSE = \sqrt{\frac{\sum(f(k)-T(k))^2}{N}} \quad (3)$$

where N is the total number of machined components.

Based on the above definitions, the energy consumption on machining the k^{th} component $E_{machining}(k)$ can be calculated below:

$$E_{machining}(k) = E_{initial} \times (1 + T(k)) \quad (4)$$

where $E_{initial}$ is energy consumption of machining the identical component with a fresh cutting tool.

Energy modelling-ANN

To support scheduling and rescheduling optimisation, energy models for components to be machined (energy modelling-ANN) have been established using a multi-layer ANN architecture. A multi-layer ANN provides several distinguishing characteristics (Li et al., 2006): (1) the capability to capture and perform complex input and output relationships; (2) no prior knowledge regarding input and output is needed to develop learning models. The trained model can enhance the knowledge database and the newly learned knowledge can refine the ANN. A fitting function is performed by the ANN and it is not necessary to define it explicitly; (3) the capability to update the ANN when new data are used. The inputs of the energy modelling-ANN are precision requirement, machining feature quantity, material and machining volume. The outputs are predicted energy consumption and machining time. The historical energy information is used to train the ANN. The design of the energy modelling-ANN is illustrated in Figure 5. In the ANN, the energy consumptions for both training and estimation are based on the conditions of tools during training time. They will be calibrated using the above tool aging factor and model to support the energy modelling process of the following scheduling and rescheduling optimisation.

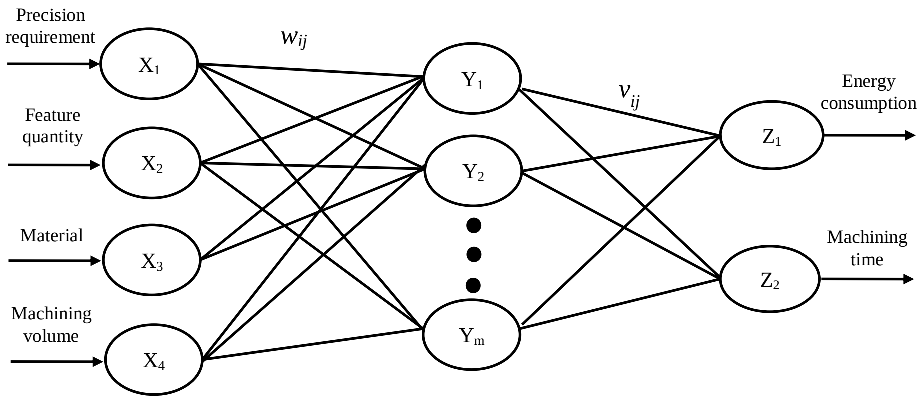


Figure 5: Design of the energy modelling-ANN.

It is important to decide a suitable training algorithm and neuron structure for the ANN to improve accuracy and computing efficiency. In the past, various training algorithms have been developed for ANNs to deal with different applications. According to the research of Drouillet et al. (2016) and Karkalos et al. (2016), Levenberg–Marquardt has the best performance (accuracy and time) when dealing with non-linear problems.

The number of hidden neurons decides the accuracy and computing time of the system. According to guidelines by Zhang et al. (1998), it is recommended that the numbers of hidden neurons are $n/2$, $1n$, $2n$, $2n + 1$, where n is the number of neurons in the input layer. The number of hidden layers also decides the accuracy and computing time of the system, a single hidden layer is sufficient for most work (Karkalos et al. 2016; Louly et al. 2017). Two hidden layers may be more accurate for some cases (Zain et al. 2010). For the energy modelling-ANN, one layer and two layers with different numbers of neurons in the hidden layer(s) are compared to decide the best structure. The comparisons are given in Section 6.3.

The trained energy modelling-ANN will be used for prediction at the beginning of production cycle. Energy data is continuously collected, the actual energy consumption for components machining will be calculated and compared with prediction result in equation 5.

$$\Delta_E = \left(\frac{E_{actual} - E_{prediction}}{E_{actual}}\right) \times 100\% \qquad (5)$$

where Δ_E is difference between the predicted results of energy models and real energy model. If difference exceeds threshold value of 5% (decided in Section 5.3), the energy modelling-ANN will be updated and reschedule will be triggered.

4.2 Energy monitoring-ANN

During a machining lifecycle, identical component operations with the same machining parameters under the same cutting should generate similar energy consumption patterns with slight deviations. Abnormal energy patterns during machining indicate significant condition changes of machines and/or tooling, thus a corresponding action such as system maintenance, rescheduling and tool changing, will be necessary.

The design of the energy monitoring-ANN is illustrated in Figure 6 and Table 4. To train the energy monitoring-ANN with energy profiles, continuously monitored energy data (power) are partitioned into a series of energy patterns according to the machining duration of each component. The monitored power consists of several stages, e.g., idle, machining, machine start-up/shutdown. The data partition process is based on the power range to concentrate on the data of the machining process. When the power is above a given threshold defining the working range for machining, the energy profiles of a component are partitioned from the monitored Big Data. An illustrative example is given in Figure 7. The input is a vector of an extracted energy samples during production, and the output is a vector representing the component operation for the input energy pattern. The vector length of the input *n* is the maximum length of power readings (maximum number of a machining process of a component). For a component operation with a smaller number of durations compared to the maximum number of duration, 0 will be added at the end of the pattern to standardise the vector lengths of the patterns to be the same, so all the data can be facilitated for ANN's processing. In terms of output, *o* is the total number of component types. For instance, if the output is for component operation 1, the output will be $[1\ 0\ 0\ \cdots\ 0]$ and the vector length of the output is the number of component operation types. P is the individual power reading, Y is the value for hidden neuron and J is the output which can indicate the types of component.

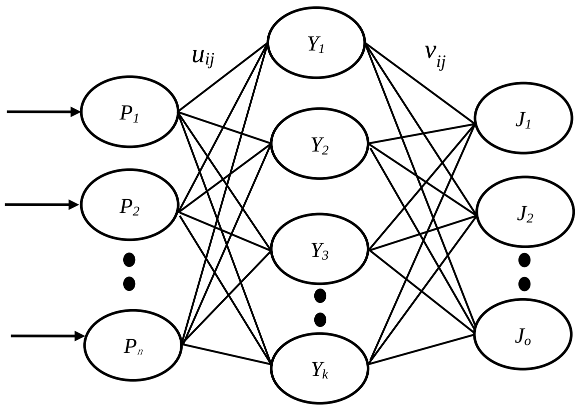
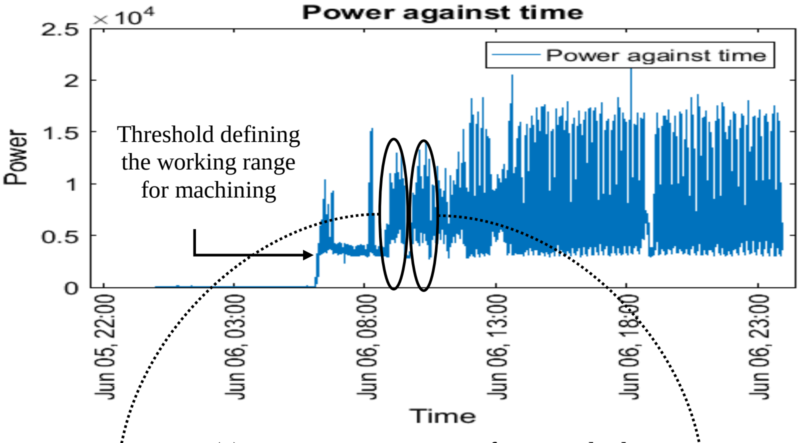


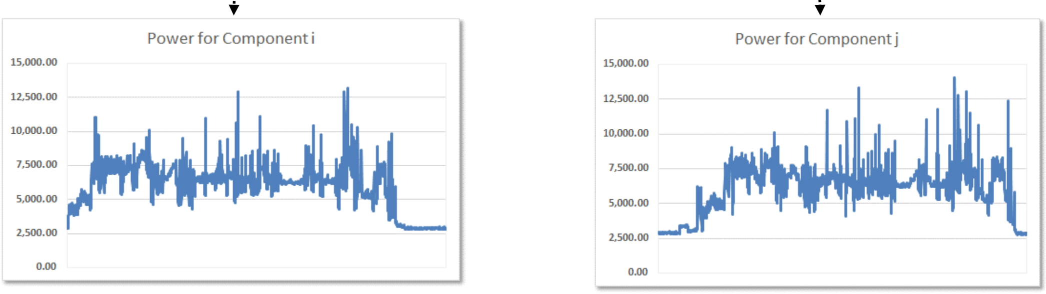
Figure 6: Design of the energy monitoring-ANN.

Table 4: Input and output of the energy monitoring-ANN.

Input vector	Output vector
Point 1 in the energy pattern	Component category 1 [1, 0, 0, …, 0]
Point 2 in the energy pattern	Component category 2 [0, 1, 0, …, 0]
… …	… …
Point n in the energy pattern	Component category o [0, 0, 0, …, 1]



(a) Energy consumption for a single day



(b) Two energy patterns for two individual components partitioned from the daily energy

Figure 7: Examples of energy partition to individual energy patterns for individual components.

The abnormal condition can be detected by calculating the deviation of the current energy pattern and the previous energy pattern for the identical component. The deviation (Δ) of energy consumption of an identical component is expressed in Equation 6.

$$\Delta = \frac{E_i - E_j}{E_j} \times 100\% \tag{6}$$

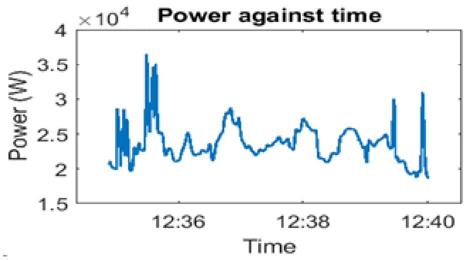
where E_i and E_j are the energy consumption of two identical components under different conditions.

If the value of deviation exceeds a large threshold (σ_{max}), which means that an abnormal condition occurs. And then a message will be sent out to the machine operator and the investigation will be carried out. If this is caused by severe aging or degrading conditions of tooling and/or machines, the machines or tools will be replaced and then rescheduling optimisation will be triggered to generate a new plan to address the current working conditions. σ_{max} is set as 18% which is obtained from the following experiment. Meanwhile, the values for individual components would be updated during machining stage when more energy data is acquired.

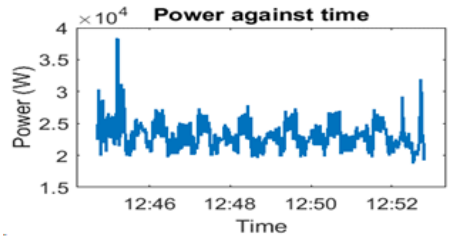
As shown in Figure 8 (a) and (b), a metal cover was selected and machined repeatedly several times. The energy consumption and surface roughness are measured and compared. According to the comparison result between the normal condition and defeat condition, shown in Figure 8 (c) and (d), respectively, it is noted that when the machine tool is in a severe wear condition, the energy deviation of the two components is 21.67%. And the surface roughness of the defeat component is 3.22μm which is much bigger than the quality standard threshold 1.15μm. Through statistic results, all the machined parts with the surface roughness meet the design requirements all have less energy deviation than 18% by comparing with the standard one. And thus, in this work, σ_{max} is set as 18% that any energy deviation higher than it will be recognised as abnormal condition.

(a) Machined component under a normal condition

(b) Machined component under an abnormal condition



(c) Power profile under a normal condition

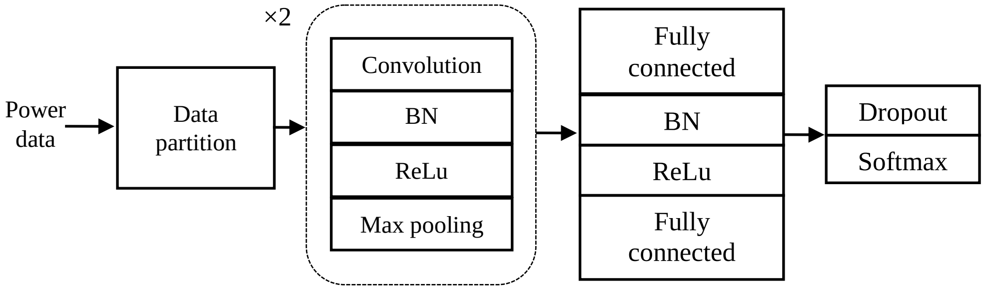


(d) Power profile under an abnormal condition

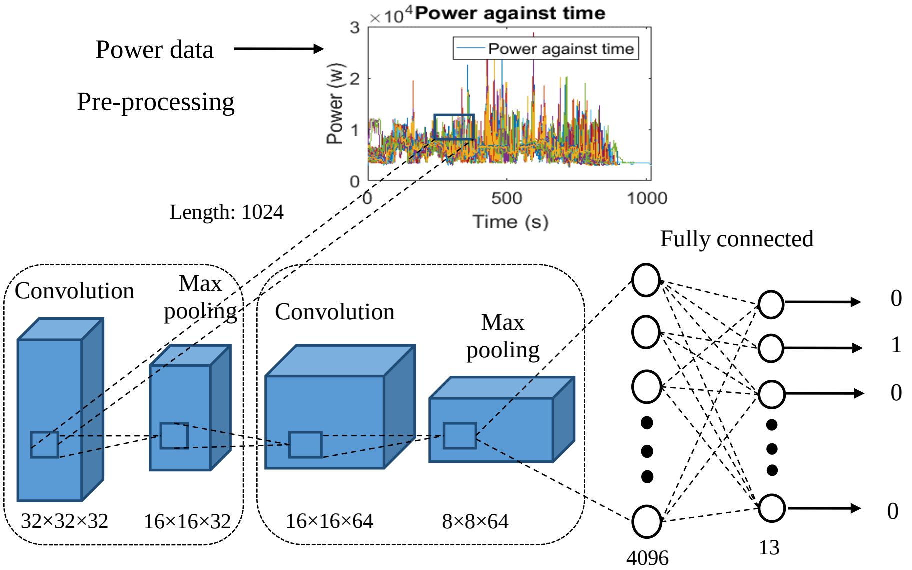
Figure 8: Power profiles for machined components under normal and abnormal conditions (energy consumptions are 2.03Kwh and 2.47Kwh respectively - the deviation is 21.67%).

4.3 Benchmarking with Convolutional Neural Network

To justify the choice of the ANNs in this research, they are benchmarked with a popular deep learning algorithm - Convolutional Neural Network (CNN). CNN is mostly used in classification research for EEG/ECG signals (Rajpurkar et al., 2017; Hosseini et al., 2017), which have the similar data format to that of power signals. The high-level structure of the CNN is depicted in Figure 9(a). In the convolution layer, neurons are connected as rectangular grids through a kernel filter with the same weights. In the pooling max layer, rectangular grids are subsampled to extract core information (Rajpurkar et al., 2017). Normally, the first layer of CNN can only extract basic information of data. The following layers are able to extract deeper information. Therefore, aiming to guarantee both accuracy and shorter computing time, convolution and max pooling are only applied twice in this case (Rajpurkar et al., 2017). The dimension of the kernel filter is selected as 2×2. For each layer between convolution and max pooling, Batch Normalisation (BN) is applied to address the saturating nonlinearities issue. An activation function ReLu is then applied to introduce nonlinearity in the model (Ioffe and Szegedy, 2015). The data are fully connected after convolution and max pooling. At the end, Dropout and Softmax are applied to avoid over-fitting and extreme values (Srivastava et al., 2014). The detailed structure of the CNN used in this benchmarking is shown in Figure 9(b). The dataset used for the ANN training is also used for training the CNN. 78 samples of component data with length of 1024 are trained in the CNN. The dimension of each layer is shown in Figure 9(b). The fully connected structure at the end is 4096-13.



(a) The high level representation of the CNN structure



(b) The detailed design of the CNN for comparison

Figure 9: Design of the CNN for comparison.

The result comparison of the ANN and CNN for the same dataset is shown in Table 3. By comparing the CNN and ANN, the CNN method can achieve 100% average accuracy, which is 1.13% higher than that of the ANN method. However, the CNN method is more time-consuming. It needs average 18.36 seconds to process a set of data, which is 8.3 times more than that of the ANN method. For a real-time processing, time is a more critical factor if the accuracy can meet application requirements. Therefore, in this research, the ANN method even with a slightly lower accuracy is considered as a better solution than the CNN method. ANN has been selected for I^{2}S.

Table 3: Comparison of ANN and CNN for this research.

Method	Average iterations	Average computing time (s)	Average accuracy (%)
ANN	9.8	1.973	98.97
CNN	15.6	18.36	100

5. Scheduling and Rescheduling Optimisation

In a shop floor, a poor and out of data scheduling plan will lead a long time machines standby and extra labour costs. Therefore, scheduling and rescheduling optimisation algorithms are vital for achieving sustainable manufacturing.

5.1 Energy, makespan and machine utilisation level

In this research, the conditions/assumptions for scheduling and rescheduling optimisation are defined as following:

- A shop floor consists of a set of CNC machines: Machine $M=\{M_1, M_2, M_3....M_n\}$, to machine a set of components: $J=\{J_1, J_2, J_3...J_m\}$;
- Each component has to be finished in a single machine when it is available;
- Each component will use different machining time and energy consumption by using different machines;
- During different lifecycle of a cutting tool, the energy consumption for machining a component will be different;
- The preparation time is assumed to be constant in the same machine;
- There are no sequencing constraints for machining components;
- The machine start-up and shut-down energy are negligible.

The energy consumption of a machine is from machining and waiting phases:

$$E_{total}(M_i) = E_{machining}(M_i) + E_{waiting}(M_i) \tag{7}$$

where $E_{total}(M_i)$ represents the energy consumed during all the phases of Machine M_i. $E_{machining}(M_i)$ and $E_{\text{waiting}}(M_i)$ represent the energy consumption of this machine during the machining and waiting phases, respectively.

For the energy consumption of Machine M_i during the machining phase is computed below:

$$E_{machining}(M_i) = \sum_{j=1}^{m}(A_{ij} \times E_{machining}(M_i, J_j)) \tag{8}$$

where A_{ij} represents whether Machine M_i needs to be machining for Component J_j. $E_{machining}(M_i, J_j)$ represents the machining energy consumption of Component J_j by Machine M_i. m is the total number of components to be machined. A_{ij} can be defined as below:

$$A_{ij} = \begin{cases} 1 & Componet\ J_j\ is\ machined\ by\ M_i \\ 0 & Componet\ J_j\ is\ not\ machined\ by\ M_i \end{cases} \tag{9}$$

For the energy consumption of Machine M_i during the waiting phase is computed below:

$$E_{waiting}(M_i) = \sum_{j=1}^{m}(A_{ij} \times E_{waiting}(M_i, J_j)) \tag{10}$$

where $E_{waiting}(M_i, J_j)$ represents the energy consumption of the machining waiting time of Machine M_i for Component J_j.

The total energy consumption for all the machining jobs by all the machines are calculated below:

$$E_{total} = \sum_{i=1}^{n} E_{total}(M_i) \tag{11}$$

where E_{total} represents the total energy consumption in all machines. n is the number of total machines.

Similarly, the time consumption for each machine during machining can be calculated as below:

$$T_{total}(M_i) = T_{machining}(M_i) + T_{waiting}(M_i) \tag{12}$$

where $T_{total}(M_i)$ represents the total time consumption during all the phases of Machine M_i. $T_{machining}(M_i)$ and $T_{waiting}(M_i)$ represent the time demand of this machine during all the machining and waiting phases, respectively.

To calculate the time used during the whole machining time: makespan, which is the maximum machining time for all the components in all the machines, can be computed below:

$$Makespan = \underset{j=1}{\overset{n}{Max}}(T_{total}(M_i)) \tag{13}$$

The balanced utilisation of machines in a shop floor is defined below:

$$\mu = \frac{\sum_{i=1}^{n} T_{total}(M_i)}{n} \tag{14}$$

$$Utlisation\_level = \sqrt{\sum_{i=1}^{n}(T_{total}(M_i) - \mu)^2} \tag{15}$$

5.2 Scheduling optimisation modelling and normalisation

In this research, the optimisation objectives are to achieve the minimised energy consumption, makespan and the most balanced utilisation level of machines. As the three objectives have very different value range, a normalisation process of the objective is required prior to optimisation. Since the maximum and minimum values of these three objectives are unknown before optimisation, a suitable normalisation schema that normalises the objectives 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 and can be obtained by minimising the i^{th} objective individually, i.e.,

$$z_i^U = f_i(x^i) = min\{f_i(x)\} \quad (16)$$

The upper bound is then obtained from the Nadir pointz_i^N , which is defined as:

$$z_i^N = f_i(x^k) = \max_{1 \ll j \leq I}\{f_i(x^j)\} \quad (17)$$

where I is the total number of objectives.

According to Equation 16 and 17, the energy consumption, makespan and machine utilisation level can be expressed in Equation 18.

$$\begin{cases} NE = (E_{total} - z_1^U)/(z_1^N - z_1^U) \\ NT = (Makespan - z_2^U)/(z_2^N - z_2^U) \\ NU = (Utilisation - z_3^U)/(z_3^N - z_3^U) \end{cases} \quad (18)$$

The fitness function is calculated as weighted sum of the three objectives below. According to research by Mausser (2006), weights of each objective are decided by decision maker based on the intrinsic knowledge of the problem. The weights will be decided in Section 6.3 for this case.

$$\text{Fitness: } \min(w_1 \cdot NE + w_2 \cdot NT + w_3 \cdot NU), w_1 + w_2 + w_3 = 1 \quad (19)$$

5.3 Optimisation algorithm

In this paper, a latest evolutional optimisation algorithm, i.e., FFO (Fruit Fly Optimisation), has been developed and improved for scheduling optimisation. FFO is a relatively new optimisation algorithm (Pan, 2012). It provides multiple fruit fly groups for parallel search during the evolution process. It is competitive compared to evolutional and other main-stream optimisation algorithms due to the local optima avoidance. The algorithm mimics the search behaviour of fruit flies with two main steps: 1) searching the locations of food sources based on smell concentration as a smell-based search, and 2) flying close to food source locations based on the highest smell concentration as a vision-based search (Zheng et al., 2014). Meanwhile, multiple groups are used for parallel and global search to achieve optimum results quickly. Based on the benchmarking analysis with other algorithms, it can be proved that this algorithm is simpler but more robust due to the advantage of a stable search route and quick convergence speed (Pan, 2012). In this research, this algorithm has been applied for schedule optimisation. Meanwhile, a mutation operation has been added into the algorithm for rescheduling optimisation.

Scheduling optimisation

During the search process, the initial group of fruit flies are swarm centres and a sub-population of fruit flies generated around the location of each swarm centre are employed for simulating the leadership hierarchy. In addition, two main steps of searching, i.e., smell-based search and vision-based search are implemented:

- Smell-based search: Sub-population of fruit flies are randomly generated around location of each swarm centre, and the smell concentration (fitness) of each fruit fly is calculated. Since the food source location is unknown, neighbourhood based search aims to implement smell-based search to approach the location of food (solution). The multi-swarm approach can avoid being trapped into local optima (Wang and Zheng 2018).
- Vision-based search: The fruit fly in sub-population with better fitness than swarm centre can replace the original swarm centre, which keeps the best smell concentration (fitness) by flying towards the food location using visions. Therefore, the food source will be approached quickly through iterations (Pan 2012).

In the conventional FFO, the initial swarm centres are generated randomly. Sub-populations of fruit flies are generated randomly around the locations of each swarm centre. However, the initial swarm centres could be far from the target, which will waste computing resources and potentially miss the best solution. In order to improve the quality of the initial swarm centres, a larger population of *M* initial fruit flies will be randomly generated and the *m* fruit flies ($M>m$) will be selected as the initial swarm centres. In Section 6.3, the optimisation results show that the improved FFO can achieve convergence quicker with better results than the conventional FFO. The process of applying the algorithm for scheduling optimisation is depicted below:

1. Initialisation: Randomly create big initial population of *M* fruit flies to be potential swarm centres, each fruit fly is composed of a matrix containing the information of components and corresponding CNC machines for machining. The matrix below illustrates an example to establish a fly (the matrix below is an example of 1 fruit fly, assuming there are 3 CNC machines to machine 9 components of 4 types for a production cycle):

$$\begin{array}{cl} \begin{bmatrix} 1 & 2 & 2 & 1 & 2 & 4 & 1 & 3 & 3 \\ 1 & 1 & 2 & 2 & 2 & 3 & 3 & 3 & 3 \end{bmatrix} & \begin{array}{l} \text{Components} \\ \text{CNC machines} \end{array} \end{array}$$

2. Swarm centres selection: Calculate the fitness of the initial *M* fruit flies. Select the *m* fruit flies with best fitness as initial swarm centres, then set the maximum iterations (T_{max}) for the optimisation computation.
3. Smell-based search: Generate 1 sub-population of *n* fruit flies around each swarm centre. The value of T_{max}, *M*, *m* and *n* are decided in Section 6.3. For the purpose of generating a fruit fly in the sub-population, crossover and mutation processes are applied based on the location of the swarm centre: Two components are randomly exchanged and one CNC machine type is randomly

switched to another CNC machine type. The fitness of each fly will be then calculated for the following vision-based search. The matrix below illustrates an example to establish a fly in a sub-population:

$$\text{Swarm centre: } \begin{array}{cl} \begin{bmatrix} 1 & 2 & 2 & 1 & 2 & 4 & 1 & 3 & 3 \\ 1 & 1 & 2 & 2 & 2 & 3 & 3 & 3 & 3 \end{bmatrix} & \begin{array}{l} \text{Components} \\ \text{CNC machines} \end{array} \end{array}$$

$$\text{1 fly in Sub-population: } \begin{array}{cl} \begin{bmatrix} 1 & 2 & 3 & 1 & 2 & 4 & 1 & 2 & 3 \\ 1 & 1 & 2 & 2 & 2 & \mathbf{2} & 3 & 3 & 3 \end{bmatrix} & \begin{array}{l} \text{Components} \\ \text{CNC machines} \end{array} \end{array}$$

4. Vision-based search: If the fitness of the fly in sub-population is better than the fitness of the swarm centre, replace the current swarm centre with the fruit fly in the sub-population. In order to avoid being trapped into a local optimal result, the probability of accepting a worse result is adopted to achieve a global optimal result when Equation 20 is satisfied (Li et al. 2015):

$$e > rand \tag{20}$$

$$e = exp(-|dC|)/Time \tag{21}$$

$$dC = fitness2 - fitness1 \tag{22}$$

where *e* represents a coefficient to determine whether the new result is accepted and can be calculated from Equations 21 and 22; *rand* is the random number between 0 and 1; *dC* represents the difference between the best fitness in the current iteration and the previous one; *Time* is the index of current iteration.

5. Repeat the above Steps 3-4 until reaching the maximum iterations. The best solution in the fly population is selected.

<u>Rescheduling optimisation during manufacturing lifecycles</u>

During manufacturing lifecycles in Stage B shown in Figure 2, energy data are continuously collected. If the difference between the predicted results of energy models and real energy model exceed the pre-defined threshold, the energy model will be updated. The FFO algorithm is also triggered to generate an optimised reschedule based on the new energy model. Inaccurate energy models could lead to faulty scheduling. According to the literature review of Soualhia et al. (2017), there is a lack of research on evaluation on deciding how accurate an energy model is required for energy efficient scheduling. In this case, the threshold is set as 5% to ensure high accurate models. In future work, an adaptive fault-tolerance-aware approach to decide the threshold will be researched.

During manufacturing lifecycles in Stage C shown in Figure 3, the energy monitoring-ANN is used for monitoring and identifying significant energy pattern change (more details of the diagnosis and prognosis processes based on the energy monitoring-ANN are presented by researchers from the same research group (Wang et al., 2018)). If the change of an energy pattern exceeds σ_{max} ($\Delta > \sigma_{max}$) and it is confirmed that there is a tool/machine problem for maintenance, the machine will be removed from the schedule plan. The FFO algorithm is triggered to generate an optimised reschedule with other available machines.

6. Industrial Applications

6.1 Design of CPS and energy Big Data infrastructure

For I^{2}S, a WSN has been developed based on IPv6 Over Low Power Wireless Personal Area Network (6LoWPAN) protocol, as illustrated in Figure 10. This wireless data acquisition system is treated as a backbone of CPS system to collect energy consumption data from a shop floor. Measured data is transmitted through the 2.4 GHz Wi-Fi to an Internet-router. Monitored energy data can be defined as Big Data, which are characterised by high volume (e.g., more than 10G volume for six-month monitoring), variability (e.g., time, machine IDs and current readings) and velocity (e.g., 9 current data samples in a second for 3-machine monitoring) (Mayer-Schonberger and Cukier, 2013). For I^{2}S, the Hadoop Hive system, a powerful Big Data storage tool, is used as the Big Data cannot be handled by traditional data platform such as MySQL. Data partition is used to split the data on component-, daily-, weekly- or monthly-basis through Map-Reduce for parallel processing of data. With the parallel storage and data processing functions, the Big Data can be processed efficiently. Due to the huge amount of data accumulation, there might be issues when importing data into Hadoop for processing: 1) data duplication due to data accumulation in sensor nodes; 2) data missing due to Wi-Fi signal interference in the shop floor. If there is data duplication or data missing, it is necessary to carry out data cleaning to remove duplicated data and make sure that data sets have the same length to train the ANNs and process data using the ANNs. The relevant process is illustrated in Figure 11.

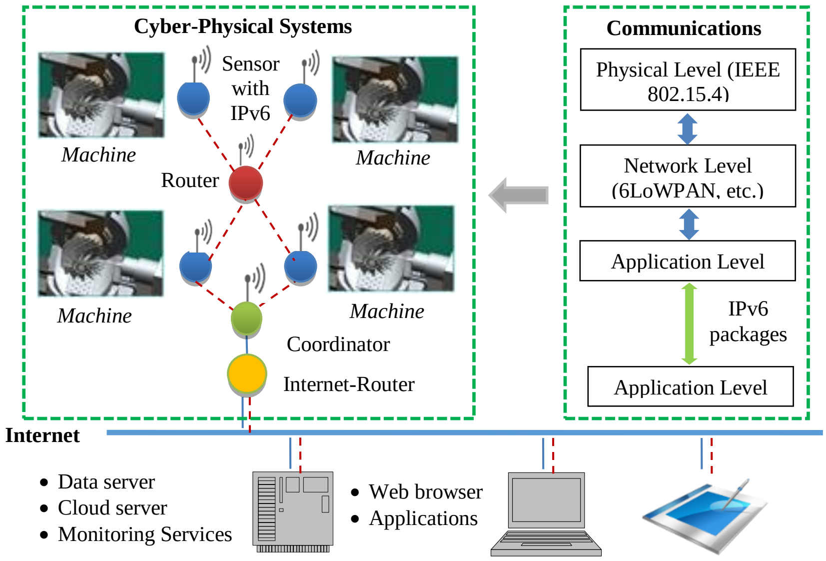


Figure 10: CPS for collecting and monitoring energy Big Data.

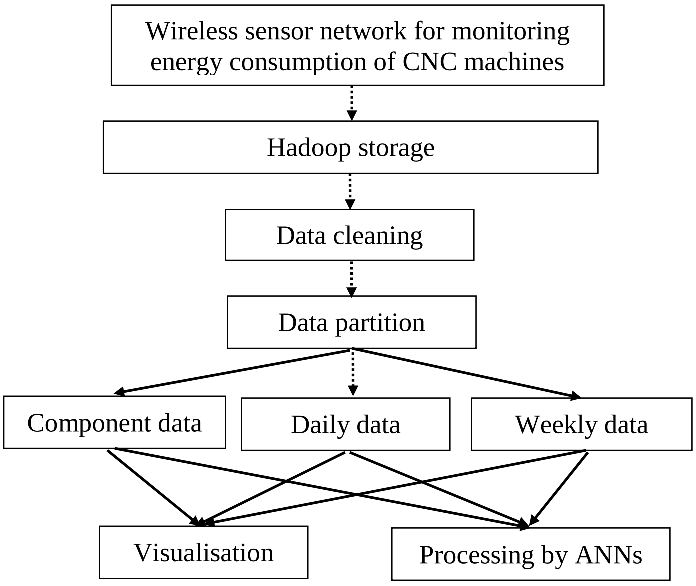
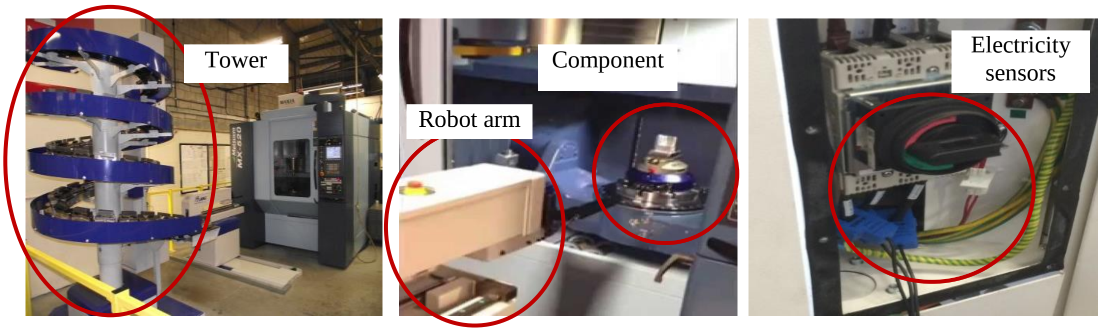


Figure 11: Design of the Big Data infrastructure.

6.2 Industrial deployment, case studies and monitored data

Sponsored by the EU Smarter and Cloudflow projects, I^{2}S has been deployed for trial in several machining companies in Europe for over 6 months respectively. An industrial deployment in the UK is described for illustration. The company specialises on machining high-precision components for automotive, aerospace and tooling applications. A production line, consisting of 3 CNC machines (MX520, MAZAK and HAAS) and accessory equipment, has been monitored, analysed and scheduling/rescheduling optimisation using I^{2}S. A part of the production line is illustrated in Figure 12. Its specifications are listed in Table 4. The CNC system is automated with Lang Eco Towers and robot arms for loading raw materials and storing completed components after machining. Electricity sensors are mounted on the CNC machines. Energy data are transferred to the Hadoop server through Wi-Fi signals in the shop floor. For each CNC machine, the collection rate of energy data is 3 readings per second. Some components to be machined are shown in Figure 13.



(a) Loading/unloading towers (b) Loading/unloading robot (c) Power measurement

Figure 12: Loading/unloading towers, robot feeding and energy measurement of CNC machines.

Table 4: Specifications of the monitored CNC machines and accessory equipment.

Machines and accessory equipment	**Specifications**			
	Max. travel (mm)	Loading capacity (kg)	Rapid traverse: X / Y / Z (m/min)	Spindle speed rev/min
MX520	630 / 560 / 510	150	40	12,000 -20,000
MAZAK VTC-800/20SR	2,000 / 800/ 720	-	50	18,000
HAAS VF-2TR	762 / 406 / 508	36.3	25.4	8100
	Handling weight (kg)	Max. workpiece size (mm)		
Lang Eco Towers	450	350 × 200 × 200		
Robot arms	30	350 × 200 × 200		

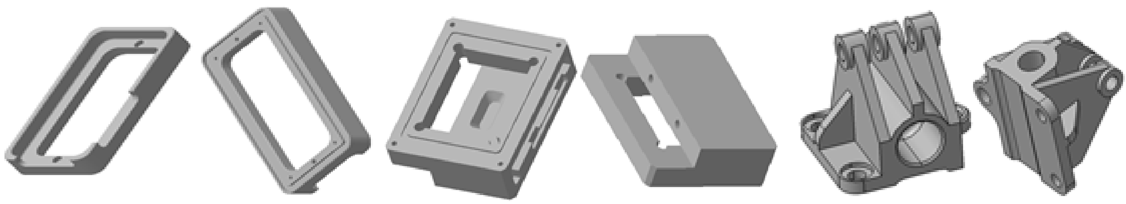
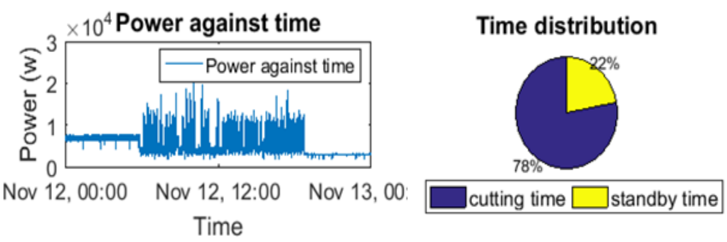
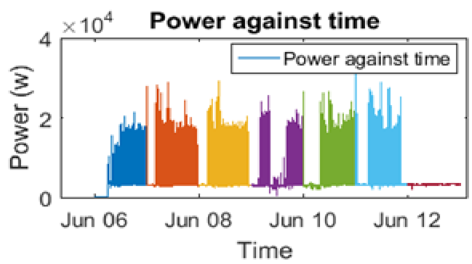


Figure 13: Some sample components.

For the monitored energy consumption data, each machine uses 3-phase electricity. The voltage is 220V and power factor is 0.82. As shown in Figure 14, daily, weekly and longer period data plots can be generated and visualised.



(a) Daily energy data plot and summary



(b) Weekly energy data plot

Figure 14: Plots of energy data and summary.

6.3 Result analysis

Energy modelling-ANN

During each production cycle, energy data are collected, and energy models are established by the energy modelling-ANN. The inputs of the ANN include precision, feature quantity and machining volume. The outputs are the predicted energy consumption and machining time to support scheduling and rescheduling optimisation. Table 5 provides results of 13 types of components and relevant estimated energy consumption and time generated by the energy modelling-ANN. Training results based on the different ANNs structures are shown in Table 6. It proves that the 4-4-2 structure has the ability to achieve convergence quickly as well as good results. Therefore, the structure can be considered as the best structure.

Table 5: Input/output of the energy modelling-ANN (calibrated under the condition of a fresh cutting tool).

Comp-onents	Prec-ision (μm)	Feature quantity	Machining volume (cm^3)	Machining time (mins)			Energy consumption (KWh)		
				MX520	MAZAK	HAAS	MX520	MAZAK	HAAS
1	2.6	7	242.3	16.5	13	27	0.405	0.443	0.565
2	2.6	11	248.7	13.5	25	37	0.812	0.546	0.932
3	2.6	19	486.6	33	28	38	2.122	1.472	2.886
4	2.6	11	353.8	21.5	24	33	1.521	1.56	1.824
5	2.6	6	462.15	33	32	43	2.203	2.533	2.912
6	2.6	4	237.3	12	22	23	0.962	1.488	1.563
7	2.6	5	392.45	27	23	32	2.423	2.13	2.733
8	2.6	2	216.1	18.5	24	11	0.863	0.845	0.996
9	2.6	9	190	10	18	17	1.135	0.729	1.765
10	2.6	20	218.2	8	19	22	1.002	0.582	1.322
11	2.6	14	260.1	9	13	16	2.201	1.685	2.531
12	2.6	14	333.2	20	26	35	1.967	1.634	2.127
13	2.6	10	295	24	23	17	2.199	2.519	2.329

Table 6: comparison for ANNs structures

Number of hidden layer	Number of neurons	Average Training time (s)	Average iterations	Average RMSE	Lowest RMSE
1	2	0.571	9.8	1.732	1.689
2	2	0.607	15	1.716	1.602
1	4	0.617	7.8	1.596	1.553
2	4	0.669	9.2	1.697	1.561
1	8	0.672	12.6	1.645	1.537
2	8	0.724	12.2	1.710	1.592
1	9	0.745	8.2	1.793	1.727
2	9	0.789	9	1.917	1.816

Tool aging model

As stated previously, the tool aging model is used to refine the model to fit for dynamic working conditions. In this work, the tool aging model based on the energy data of the 52 consecutive machining has been developed. The cutting volume for a component is equal to 305.6cm^3. The energy consumption for machining the component with a fresh cutting tool is 1.365Kwh (the cutting tool is CoroMill® Plura Optimised). As shown in Figure 15, the tool aging factor gradually increases over production time, which means the tool is gradually wear over machining lifecycles. Based on Equations 1-3 and RMSE minimisation optimisation, the tool aging model is established below:

$$T(k) = 0.2199 \times k^{0.1363} - 0.1952 \tag{23}$$

The aging model has been evaluated through more experiments by comparing with the prediction value to the true value. The results are depicted in Figure 15. The average of RMSE is around 0.0135 which is demonstrated the tool aging model has high accuracy to reflect the tool aging condition.

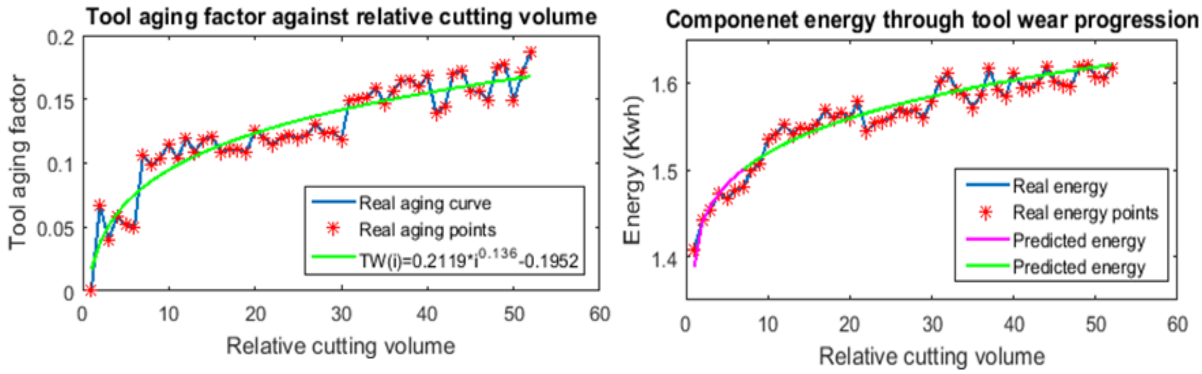


Figure 15: Tool aging model (left) and validation (right).

Energy monitoring-ANN

13 types of components with total 78 energy pattern samples have been used to train the energy monitoring-ANN. Some results are shown in Table 7. It indicates that the structure with 512 neurons and 1 middle layer has achieved the best performance in terms of average accuracy, the highest average accuracy and the shortest training time. Therefore, it has been selected for this ANN design. Meanwhile, in the previous Section 4.2, the ANN has been compared with CNN to indicate its effectiveness and advantage to support I^2S.

Table 7: Comparisons of different ANNs' structure.

Number of layer	Number of neurons	Average Training time (s)	Average iterations	Average accuracy (%)	Highest accuracy (%)
1	512	1.973	26.6	98.97	100
2	512	3.244	30.2	98.69	100
1	1024	4.018	27.6	97.69	100
2	1024	8.475	31	96.92	100
1	2048	6.711	26	98.46	100
2	2048	19.964	23.6	96.92	100
1	2049	7.703	29.2	98.97	100
2	2049	24.169	30.6	98.20	100

Scheduling/rescheduling Optimisation

In this paper, improved FFO, conventional FFO, Genetic Algorithm (GA) and Simulated Annealing (SA) have been benchmarked to indicate the performance. Simulations have been run for 10 times for each algorithm to compare the average results. Based on performance criteria, Energy consumption and machine utilisation level are optimised simultaneously. Therefore, w_1, w_2 and w_3 are 0.5, 0 and 0.5, respectively (Li et al. 2015). Figure 16 shows the optimisation results by improved FFO, traditional FFO, GA and SA respectively. According to recommendation of Zheng et al. (2014), size of sub-population is most critical parameter, number of swarm centre is not necessary to be large to avoid over focus. Therefore, the value for T_{max} (maximum iterations), M (size of initial population), m (size of swarm centre population) and n (size of sub-population) are 500, 5, 1 and 70, respectively. Detailed results are shown in Table 8.

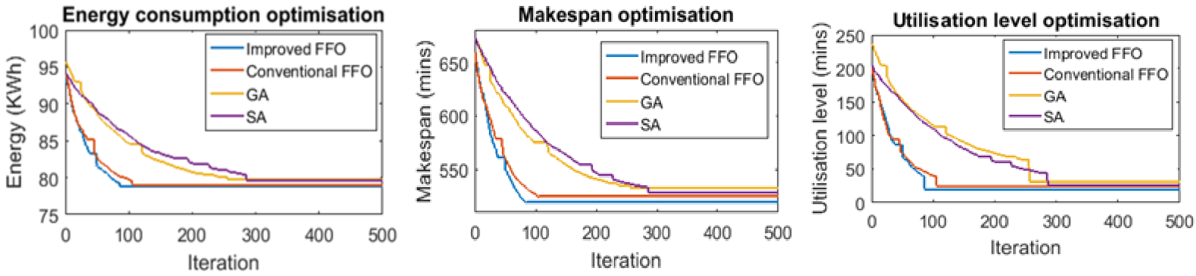


Figure 16: Optimisation results of scheduling.

Table 8: Comparisons of optimisation algorithms.

		Improved FFO	Traditional FFO	GA	SA
	Iterations to achieve optimal result	85	106	256	286
Energy consumption	Initial value (Kwh)	130	130	130	130
	Optimised value (Kwh)	78.86	78.99	79.78	79.69
	Optimisation percentage (%)	**39.34**	39.24	38.63	38.7
Makespan	Initial value (mins)	750	750	750	750
	Optimised value (mins)	520.17	525.32	533.27	527.99
	Optimisation percentage (%)	**30.64**	29.96	28.9	29.6
Utilisation level	Initial value (mins)	250.47	250.47	250.47	250.47
	Optimised value (mins)	20.33	24.97	31.64	25.77
	Optimisation percentage (%)	**91.88**	90.03	87.37	89.71

In the company, the initial energy consumption, makespan and machine utilisation level for the same production are 130 Kwh, 750 mins and 250.47 mins respectively. According to the table, improved FFO has the best system performance by examining three indicators that are 39.34% energy consumption saving, 30.64% makespan reduction and 91.88% utilisation level improvement.

The utilisation level optimised by improved FFO is less than 20.33 mins, which means all the three machines are relatively equally engaged in machining during the production cycle. Furthermore, it can be seen from the figures that the best optimised results for improved FFO can be achieved within 90 iterations, which converges faster than GA and SA. Therefore, it can be summarised that the improved FFO has good robustness for solving this scheduling problem. After over 6 months of system deployment into the company, the company has achieved about 1926.4kwh energy saving (40.3%) and 29.6% productivity improvement in total.

7. Conclusions

In this research, CPS, Big Data analytics and optimisation algorithm have been effectively integrated for energy efficient machining optimisation. The developed system is innovated in the aspects of: (1) a novel process of “scheduling, monitoring and rescheduling” to enhance adaptability to dynamics during machining lifecycles, (2) an innovative energy model over a tooling lifecycle to support energy efficient optimisation, (3) an effective evolutional algorithm FFO to generate an energy efficient schedule, and reschedule when significantly varying working conditions are monitored and adjustments on the schedule are necessary, (4) successful deployment and trial of the system into European machining companies to achieve around 40% energy saving and 30% productivity improvement in the companies. The result analysis on the system applied to a UK company given in this paper showcases the effectiveness and potential of system applicability in practice.

For future research, error processing on monitored data (data loss, data duplication) could be a very significant issue. Though some measures such as data cleaning has been integrated, more measures to eliminate the error effects need to be further investigated. In the meantime, longer-term experiments should be carried out to further validate the models developed in this research.

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