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# Big Data Enabled Intelligent Immune System for Energy Efficient Manufacturing Management

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**Abstract**

The Big Data driven approach has become a new trend for manufacturing optimisation. In this paper, an innovative Big Data enabled Intelligent Immune System ($I^2S$) has been developed to monitor, analyse and optimise machining processes over lifecycles in order to achieve energy efficient manufacturing. There are two major functions in $I^2S$: (1) an Artificial Neural Networks (ANNs)-based algorithm and statistical analysis tools are used to identify the abnormal electricity consumption patterns of manufactured components from monitored Big Data. An intelligent immune mechanism is devised to adapt to the condition changes and process dynamics of machining systems; (2) a re-scheduling algorithm is triggered if abnormal manufacturing conditions are detected thereby achieving multi-objective optimisation in terms of energy consumption and manufacturing performance. In this research, Computer Numerical Controlled (CNC) machining processes and industrial case studies have been used for system validation. The novelty of $I^2S$ is that Big Data analytics and intelligent immune mechanisms have been integrated systematically to achieve condition monitoring, analysis and energy efficient optimisation over manufacturing execution lifecycles. The applicability of the system has been validated by multiple industrial trials in European factories. Around 30% energy saving and over 50% productivity improvement have been achieved by adopting $I^2S$ in the factories.

**Keywords**: Big Data, Intelligent immune mechanism, Energy efficient manufacturing, CNC machining

## 1. Introduction

Ambitious goals to achieve significant energy savings in manufacturing have been widely set by major economies such as Europe, China and USA (Stark et al., 2017). Recent research has summarised that the energy efficiency indicators of manufacturing on a national or sectional level have been defined, but relevant sustainable process management solutions for companies have not been effectively implemented. There is a strong need to foster the relevant empirical applied research in manufacturing companies (Engert et al., 2016).

In a manufacturing shop floor, dynamics during manufacturing execution lifecycles are major challenges preventing companies from maintaining the best energy performance as well as manufacturing quality and productivity. The current management systems like process planning, scheduling and execution systems used in European factories are based on relatively static manufacturing information as a cascading decision making process (ElMaraghy and Nassehi, 2016). On the other hand, dynamics could be from various aspects of manufacturing execution lifecycles, such as frequent job order or priority changes, ambient working conditions, and unexpected delays. Manufacturing systems and tooling are also prone to aging and degrading, resulting in dimensional and geometric deviations of manufactured components. The dynamics generate unexpected breaks and unnecessary inspection, standby, repairing and maintenance of manufacturing systems, leading to time, energy and resource waste (Wang et al., 2015). To address dynamics in manufacturing, smart sensors, Cyber Physical System (CPS) and Big Data analytics have been increasingly deployed in industrial shop floors to support condition monitoring and diagnosis (Monostori et al., 2016). However, due to the large quantities of monitored data and diverse manufacturing models, relevant data collection and analysis to support energy efficient manufacturing are still inefficient and error-prone.

In this paper, an innovative Big Data enabled Intelligent Immune System ($I^2S$) has been designed to achieve energy efficient manufacturing optimisation via energy monitoring, analysis and manufacturing re-scheduling. Different from conventional management approaches that are based on pre-defined manufacturing conditions, $I^2S$ is enabled by CPS to collect energy (electricity) consumption data of manufacturing processes so as to monitor the dynamics and condition changes of the manufacturing systems efficiently. Artificial Neural Networks (ANNs)-based algorithms and statistical analytics tools are used to identify the energy consumption patterns of manufactured components. An artificial immune mechanism is then applied to counter significantly varying conditions during the lifecycle of the manufacturing process. A re-scheduling adjustment is triggered if necessary thereby achieving energy savings and maintaining optimised performance (productivity and balanced level of machine utilisation) for an entire manufacturing execution lifecycle. In this research, Computer Numerical Controlled (CNC) machining processes have been used for system development, validation and industrial deployment.

The research innovations and characteristics of $I^2S$ are below:

- The CPS, ANNs, immune mechanism and re-scheduling optimisation algorithm have been effectively integrated as innovative manufacturing intelligence to support energy efficient optimisation over manufacturing execution lifecycles. The immune mechanism has been designed to address abnormal working conditions in a systematic means;
- The collected energy data from machining systems are stored as “Big Data”, owing to the long time and high frequency of electricity data collection (i.e., 3-V features for Big Data – high Volume of collected data, high Velocity of collecting data, and high Variety of data patterns generated from different machined components). Deep learning and Convolutional Neural Networks (CNNs) are the state-of-the-art artificial intelligent technologies for Big Data processing (Yann, et al., 2015). However, their disadvantages are the requirements of long time, high computational power (GPU)

and large training sets (Najafabadi et al., 2015). To meet industrial requirements, in this research, a "divide and conquer" strategy has been designed to improve the efficiency and robustness of Big Data analysis. That is, the energy Big Data has been pre-processed and partitioned, and three-layer ANNs and statistical analysis tools have been introduced to learn and distinguish patterns efficiently so as to support abnormal condition processing;

- $I^2S$ has been validated through real-world industrial deployment into some European machining companies located in Sweden, U.K. and Spain for over six months respectively to demonstrate the significant potentials of the system's applicability in practice. Significant sustainability improvements on the environmental, economic and social aspects have been achieved by adopting $I^2S$ into the European factories (less unexpected breaks and scheduling optimisation to improve energy efficiency and productivity, intelligent monitoring and prognosis to avoid tedious human intervention and errors).

## 2. Literature Survey

Scheduling is a critical decision-making stage in manufacturing to minimise lifecycle cost, enhance adaptability to manufacturing and improve manufacturing sustainability. In the past decades, scheduling optimisation has been widely researched (comprehensive surveys have been made by Wang and Shen (2007), Li and McMahon (2007), respectively). In the research, optimisation objectives are from the aspects of lead-time, makespan and cost minimisation, and/or the most balanced utilisation level of machines. In recent years, in line with the trend on achieving sustainability in manufacturing management, energy efficiency has been increasingly considered as an important optimisation objective. Based on various developed energy models, scheduling optimisation algorithms have been developed and applied to improve the energy efficiency of manufacturing processes (Wang et al., 2014). An improved Particle Swarm Optimisation (PSO) approach was designed to address dynamic scheduling under unexpected disruptions to reduce energy consumption and makespan simultaneously (Tang et al., 2016). A new multi-objective Genetic Algorithm (GA) and NSGA-II algorithm was developed to minimise the total non-processing electricity consumption and total weighted tardiness (Liu et al., 2016). In the algorithm, a function for parent and children combination and elitism to improve optimisation further was developed. In the work of Yan et al. (2016), based on a multi-level energy model and grey relational analysis to optimise machining parameters, a GA was developed to optimise the makespan and energy consumption. Based on real-time monitored data, an enhanced Pareto-based bee algorithm was designed to optimise energy consumption and productivity (Xu et al., 2016). Salido et al. (2017) developed a memetic algorithm to minimise energy consumption under makespan constraints. However, the above research is based on relatively static machining resource information (e.g., the optimisation algorithms are based on prior experimental results before manufacturing execution) so that dynamics during manufacturing execution lifecycle are unable to be considered effectively (e.g., machining resources and working conditions are assumed unchanged though there are various ambient elements and job dynamics during the execution lifecycle of customised production). To overcome the limit, Cai et al. (2016) designed an intelligent immune algorithm that is analogous to the biological immune mechanism to eliminate disturbances produced during manufacturing scheduling operations. In the research, a framework to map an intelligent manufacturing process into an artificial immune system was developed. Based on the biological immune system that potentially offers interesting features to face the threats (bacteria, viruses, cancers, etc.), Darmoul et al. (2017) investigated the application of intelligent immune algorithms to monitor and control manufacturing systems at the occurrence of disruptions. However, the above immune works are not employed to practical applications yet. Meanwhile, the reported immune systems are based on a Non-self/Self (N/S) mechanism, which considers non-self elements as problems. This mechanism is not flexible enough to effectively process various dynamics of manufacturing processes (analysis is given in Section 4.2). A summary of the above related research is given in Table 1.

Another trend is to use in-process monitoring data and Big Data analytics for manufacturing optimisation such as scheduling and condition-based maintenance to achieve manufacturing lifecycle optimisation. A review of data mining technologies applied to manufacturing was given by Choudharya et al. (2009). A new scheduling system for selecting dispatching rules in real time by combining the techniques of simulation, data mining, and statistical process control charts was developed (Metan et al., 2010). In the research, the developed scheduling system extracts knowledge from data coming from manufacturing environments. The knowledge provides the system the adaptiveness to changing manufacturing environment and enhanced adaptability and quality of its decisions. Data analytics were also developed for condition-based maintenance and real-time manufacturing optimisation. A data mining technique to conduct logical analysis of data for condition-based maintenance was proposed by Bennane and Yacout (2012). Kusiak and Verma (2012) established ANNs to identify bearing faults in wind turbines based on real-time data. An anomaly detection-based data mining approach was developed to discriminate defect examples of rolling-element bearing failures (Purarjomandlangrudi et al., 2014). Two features, i.e., kurtosis and Non-Gaussianity Score (NGS), are extracted to develop anomaly detection algorithms. Lee et al. (2013) summarised the latest advances and trends in predictive manufacturing systems in a Big Data environment. Nevertheless, the above works have not actually been designed for processing "Big Data" sets (the data are still primarily based on limited experimental data). A Big Data conceptual architecture for cleaner manufacturing and maintenance processes of complex products was proposed by Zhang et al. (2017). Detailed design and industrial applications for specific machining processes, however, have not been reported.

Based on the literature survey and industrial survey conducted during some latest research projects by the authors, the following research gaps have been identified:

- For CNC machining execution lifecycles, there are lacking systematic integration of Big Data collection, analytics and manufacturing re-scheduling optimisation to address various dynamic working conditions adaptively for achieving energy efficient optimisation;

- Majority of the developed systems are still in laboratorial environments while industrial deployment and validation by using industrial case studies to prove the applicability of the systems to practical applications are imperative.

The goals of $I^2S$ are: (1) to design and integrate Big Data analytics and intelligent immune mechanisms, hence to conduct condition monitoring, analysis and energy efficient optimisation over manufacturing lifecycles systematically, and (2) to prove its industrial applicability through system deployment into manufacturing companies.

Table 1: Recent research for sustainable and lifecycle manufacturing.

| Works | Input | Optimisation targets | Research methods |
|---|---|---|---|
| Metan et al. (2010) | Data coming from the manufacturing environment | Average tardiness minimisation | Process control charts to monitor and update the performance of the decision tree |
| 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 |
| Purarjomand langrudi et al. (2014) | Monitoring data for rolling-element bearing failures | Minimisation of failure rate | Kurtosis and Non-Gaussianity Score (NGS) |
| Wang et al. (2015) | Spindle speed, machining speed, depth of cut and width of cut<br>Number of machines and the number of jobs to be processed | Surface quality, energy consumption and machining removal rate<br>Energy consumption for idle, working, tool change and set-up | ANNs to establish a model for surface quality and energy consumption<br>Empirical models for idle, working, tool change and set-up |
| Yan et al. (2016) | Material removal rate, spindle speed<br>Number of machines and the number of jobs to be processed | Idle power and operation power, energy consumption for processing<br>set-up, transportation, standby, and overhead | Off-line experiments for grey relational analysis<br>Empirical models for processing, set-up, transportation, standby and overhead |
| Dai et al. (2016) | Manufacturing components, sequences, manufacturing resources | Schedule, process planning | Non-Self/Self immune system, Artificial Neural Networks |

| | | | |
|---|---|---|---|
| Darmoul et al. (2016) | Material unavailability, resource failures, unavailability of operators, rush orders | Monitoring and control of manufacturing systems at the occurrence of disruptions | Non-Self/Self immune system framework |

## 3. System Framework

For a machining process, it is usually managed as a series of production cycles. During each cycle, the types of components for production are certain while the quantities of each component for production could be varying. When a new production cycle starts, the types of components will be adjusted. That is, new types may be added for machining during this cycle and old types during the last cycle may be discontinued. For such a cycle, it requires optimised scheduling for multiple components to be machined in multiple machines to achieve good energy and manufacturing performance. Due to disruption and uncertainty during manufacturing execution lifecycles (e.g., dynamic changes of job priority, unexpected delay, aging or degrading of tooling and machines), it is essential to update scheduling adaptively (i.e., re-scheduling) when machining conditions are changed. $I^2S$, which supports the above process, consists of the following functions (also shown in Figure 1):

- Vibration or acoustic sensors have been frequently used for machine condition monitoring. In this research, an electricity sensors-based Wireless Sensor Network (WSN) is integrated with CNC machines as a CPS for measuring the energy consumption of the CNC machines. The underlying consideration is that, in comparison with vibration and acoustic sensors, the developed electricity measurement sensors-based WSN is more flexible in terms of configuration and deployment. Experiments show that the energy consumption status can reflect machine and tooling conditions effectively (Zhou et al., 2016). In this research, the electricity Big Data is used to support not only energy consumption optimisation but also machine condition monitoring to address dynamics of machining processes. A Big Data infrastructure has been developed for collecting, storing and processing the real-time energy data from CNC machines;
- $I^2S$ defines an innovative architecture for manufacturing execution lifecycle. That is, a machining cycle is divided into two stages: learning at beginning, followed by execution:
  (1) During the learning stage, typical components are machined to generate energy consumption patterns of machining components for ANNs' training. Two ANNs, i.e., energy modelling-ANNs and component classification-ANNs, are trained. The two ANNs are designed to model the energy consumptions for machined components and to monitor the energy patterns of the machining components respectively. A scheduling optimisation, which is based on the energy modelling-ANNs, will generate an optimised scheduling plan to support the execution stage. The learning stage and the set-up of the relevant energy modelling-ANNs is reported by the authors' research group (Liang et al. 2017);
  (2) During the execution stage, with the support of the component energy classification-ANNs, $I^2S$ is used to analyse and process monitored energy data to address various dynamic conditions

over machining execution lifecycles. A re-scheduling optimisation will be employed to generate an optimised re-scheduling plan whenever significantly different energy patterns are identified which indicate the necessity of adjusting manufacturing plans. The details of the execution stage will be introduced in detail in this paper.

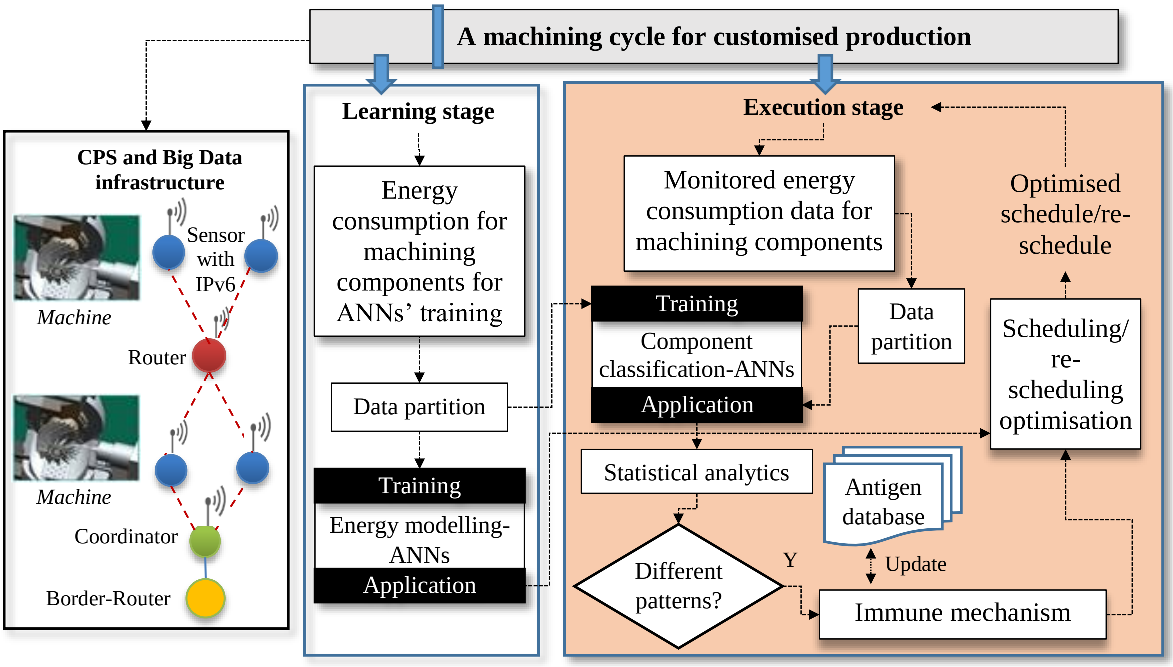



Figure 1: I$^2$S for monitoring, analysing and optimising manufacturing for energy efficiency.

## 4. Intelligent Immune Mechanism

### 4.1 Processing of monitored energy data

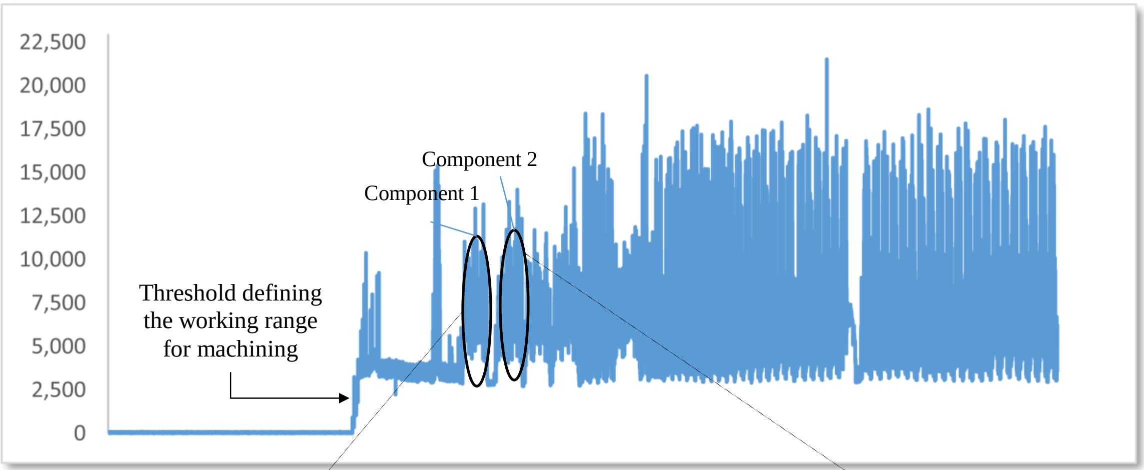
During the execution stage, the machining operations of identical components should generate similar energy consumption patterns with slight deviations. Abnormal energy patterns indicate significant condition changes of machines and/or tooling. As thus, a need for machine maintenance or tooling replacement is necessary, leading to re-scheduling optimisation.

For Big Data processing, deep learning and CNNs have pros and are also limited in terms of complex computing, high computational power requirement (GPU) and large training sets (Najafabadi et al., 2015). In I$^2$S, a "divide and conquer" strategy has been designed to improve the efficiency and robustness of the energy Big Data analysis: partitioning energy Big Data into component level-energy data, training the component classification-ANNs and conducting statistical analysis on energy pattern deviations to support intelligent immune and optimisation processes.

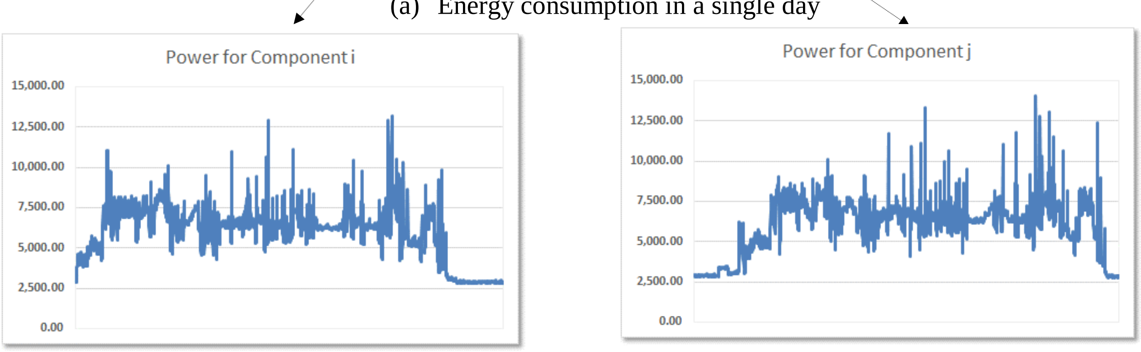
Energy data partition

As illustrated in Figure 2, to support the component classification-ANNs and further statistical analytics for energy deviation, monitored energy data are partitioned into a series of energy patterns for machining individual components. The partition process is below:

- The energy data consist of several stages, e.g., machine start-up/shut-down, idle, machining, component loading/unloading into a CNC machine. The data partition process is based on the power range and thresholds to separate these different stages. The ranges and thresholds for specific machines and materials are determined via experiments;
- During the process of machining two consecutive components, there is a stage for unloading the component when its machining process has been completed, and for loading a new component for machining. Based on ranges and relevant thresholds of unloading/loading, the energy data of machining each component are partitioned from the monitored Big Data.




(a) Energy consumption in a single day




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

Figure 2: Examples of energy partition into individual energy patterns for individual components.

<u>Training and application of the component classification-ANNs</u>

- The component classification-ANNs is a three-layer Multi-Layer Feed-Forward neural networks (MLFF) with a back-propagation learning algorithm. It is used to classify the partitioned energy data of machining components, so as to support the analysis on energy deviation conditions.
- The ANNs design is illustrated in Figure 3 and Table 2. The training data for this ANNs are from the learning stage. The input is a vector of the energy input of machining each component (e.g., three points for one second), and the output is a vector representing a component category for the input energy pattern. The vector length of the input *n* is the maximum length of each pattern. For a

component with a smaller length, 0 will be added at the end of the pattern to standardise the vector lengths of all the patterns to be in the same length to facilitate the ANNs' processing. In terms of output, *o* is the total number of component types. For instance, if the output is for Component 1, the output will be [$1\ 0\ 0 \cdots 0$]. The details of the ANNs design are explained in Section 5.

- If a pattern for a component is judged significantly different from its standard pattern of the component, the pattern will be further processed by using the immune process described later on.

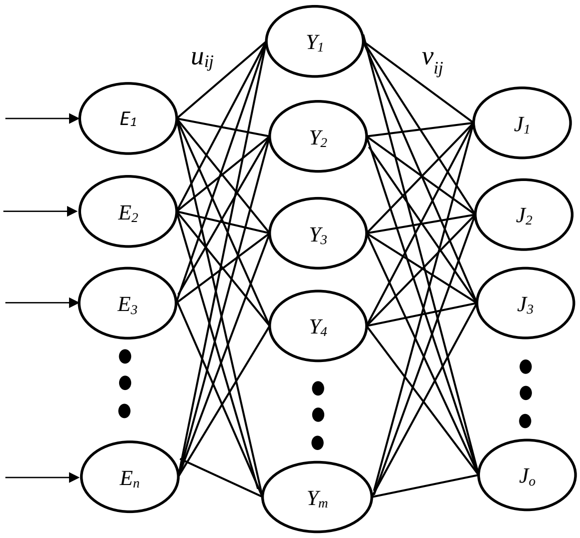



Figure 3: Design of the component energy classification-ANNs.

Table 2: Input and output of the component energy classification-ANNs.

| Input vector | Output vector |
|---|---|
| Energy input point *1* | Component category *1* [*1, 0, 0, …, 0*] |
| Energy input point *2* | Component category *2* [*0, 1, 0, …, 0*] |
| Energy input point *3* | Component category *3* [*0, 0, 1, …, 0*] |
| … … | … … |
| Energy input point *n* | Component category *o* [*0, 0, 0, …, 1*] |

### 4.2 The immune mechanism

As indicated in the literature survey, inspired by biological immune mechanisms, there are some studies on applications of intelligent immune mechanisms for manufacturing systems recently (Darmoul et al., 2013; Cai et al., 2016). The research is based on a N/S (Non-self/Self) immune mechanism, which distinguishes what belongs to the body, i.e., the self, from what is foreign to the body, i.e., the non-self for problem identification. However, N/S has the following limitations (Silva and Dasgupta, 2016):

- The research works have been designed as conceptual frameworks and they are not reported to apply to practical processes yet.

- Noises generated during the machining processes, and various dynamics of machining processes, could lead to new energy consumption patterns, which are not necessarily judged as problems. The N/S mechanism is rigid, which hinders the robustness and accuracy of the immune process.
- The machining system changes over its lifetime (analogous to the human body's aging process), the N/S immune mechanism does not take into account such self changes.

A danger theory is a more flexible immune mechanism (Silva and Dasgupta, 2016). In I$^2$S, an innovative danger theory-based immune mechanism has been designed to monitor, analyse and control machining systems at the occurrence of disruption during machining processes. Key concepts and processes are below (also illustrated in Figure 4):

- Antigens – in an immune mechanism, an antigen presents the characterising features of problems from machines, tooling and/or jobs, such as tool wear, spindle failure, machine breakdown, rush order/order modification/cancellation, control system failure, timing anomaly, etc.
- Danger signals - for the temporal series of energy consumption of the machining system functioning over time (monitored Big Data), anomalies are automatically detected from the temporal analysis of energy consumption to determine whether deviations exceed tolerable variations in an energy consumption pattern. If danger signals are matched with pre-defined antigens, they are processed accordingly. For danger signals that do not match any samples in the antigen databases in its danger zone, the danger signals will be reported to engineers for problem identification. The relevant antigen databases are updated accordingly.
- Danger zone – each component is associated with a danger zone, which constrains the working scope of matching between danger signals and antigen databases for the zone. Within a danger zone, the component classification-ANNs and statistical analytics are used for danger signal identification.
- Antibody and re-scheduling optimisation algorithm – to handle abnormal conditions detected as antigens and carry out re-scheduling optimisation if necessary.

<u>Danger signal detection (antigen detection)</u>

The anomaly detection process consists of two steps: (1) detecting anomalies by inputting the monitored energy data to the component classification-ANNs. If it is aligned with the standard energy patterns of corresponding components within the similarity threshold, it is judged that there is no anomaly detected and the system will do nothing. Otherwise, the newly input energy pattern is classified as anomalousness and the energy consumption pattern needs to be further analysed in the second step; (2) comparing the pre-defined statistical metrics between the new pattern and the normal (standard) patterns to identify the types of potential danger signals:

- Machine breakdown - no energy consumption incurred.

- Machine not working - the energy of machining a component is close to or below the standby energy for a long duration.
- Machine over-consumption and under-consumption - the power exceeds the machine-specific limits;
- Tool wear - level shift up (vertical shift up) of the energy during machining, but the energy during idle is kept unchanged;
- Cutter breakdown - energy consumption during material removal is close to that of air cutting.
- Spindle failure - energy spike unaccompanied by shift in spindle Rotation Per Minute (RPM), followed by increased energy for machining the component and then idle energy.
- Timing anomaly of control system - unexpected time shift (horizontal shift) of energy pattern between different stages.
- Rush order, new patterns - due to customised production, there are new energy consumption patterns generated which are different from the previous patterns leading to new danger signal generation.
- Order modification, order cancellation - unexpected energy consumption patterns against the original scheduled plan.

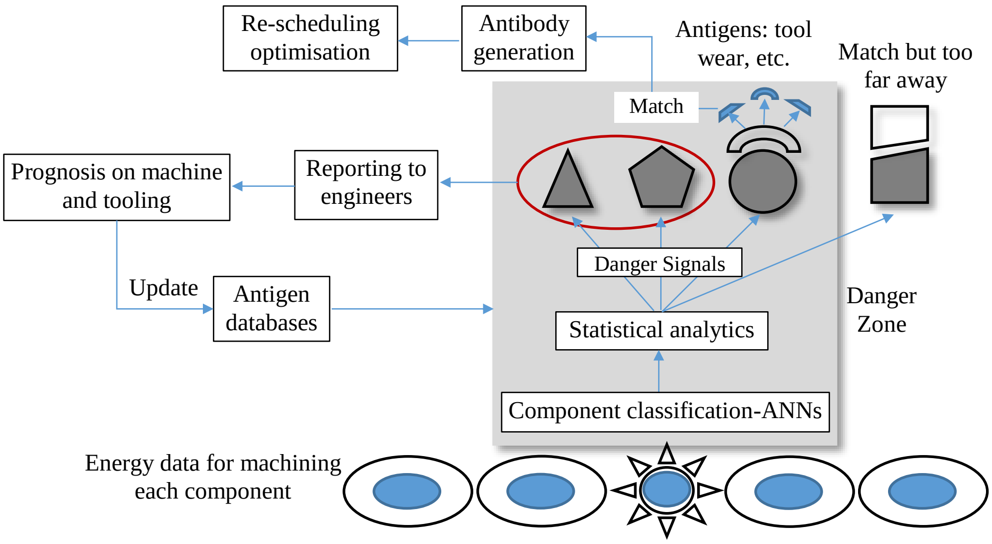



Figure 4: The danger theory-based I$^2$S framework.

In order to identify the potential danger signals in the measured energy pattern $S_{measure}$ against a standard pattern $S_{standard}$, different statistical metrics in time domain are calculated and measures are applied to determine the anomaly type. The details are given below.

Lower bound ($P_L$) and upper bound ($P_U$) of a standard energy pattern for machining a component - these are the bounds of possible powers for a specific machine to make the component. If the total number of measured power points at the machining stage for a component exceeds its bounds by a certain level (e.g., 10%), or the continuous duration of measured power outside the bounds is more than a specific number (e.g., 5), it is treated as over-consumption or under-consumption for machining this component. The definition is given in Eq. 1.

$$\begin{cases} \frac{Number\ of\ (S_{measure}(i,i=1:N1)>P_U)}{N1} > 10\% \ \rightarrow over-consumption \\ Number\ of\ continuous\ points\ (S_{measure}(i,i=1:N1) > P_U) > 5 \ \rightarrow over-consumption \\ \frac{Number\ of\ (S_{measure}(i,i=1:N1))<P_L)}{N1} > 10\% \ \rightarrow under-consumption \\ Number\ of\ continuous\ point\ (S_{measure}(i,i=1:N1) < P_L) > 5 \ \rightarrow under-consumption \end{cases} \quad (1)$$

Where $N_1$ is the total number of the measured power points in $S_{measure}$.

Limit of the standby duration - it is defined as the maximum continuous standby duration when the machine is treated as on normal operations. If the continuous standby duration of the measured power at the machining stage exceeds the limit, a non-working alarm will be sent out for further check (e.g., the machine door is not properly closed or a cutter is broken down). Based on the results of experiments, it is defined as 60 seconds in $I^2S$.

Cross-correction coefficient $X_{coef}$ - cross-correlation takes one pattern ($S_{measure}$), and compares it with a shifted pattern ($S_{standard}$). The cross-covariance between the pair of patterns ($\sigma_{Smeasure,Sstandard}$) is defined below:

$$\sigma_{Smeasure,Sstandard}(T) = \frac{1}{N-1}\sum_{t=1}^{N}(S_{measure}\ (t-T) - \mu_{measure})((S_{measure}(t) - \mu_{standard}) \quad (2)$$

Where $\mu_{measure}$ and $\mu_{standard}$ are the means of time series. $N$ is the bigger number of the samples of the two patterns. Zero-padding the shorter pattern is to make the two patterns the same length before calculation.

The values of cross-covariance at different time shifts $\sigma(T, T=1:N))$ are then calculated and normalised by the variance of each pattern as the cross-correction coefficients:

$$X_{coef} = \max(X_{coef}(T, T=1:N)) = \frac{\sigma_{s_{measure}s_{standard}}(T,T=1:N)}{\sqrt{\sigma_{s_{measure}s_{measure}}(0)\sigma_{s_{standard}s_{standard}}(0)}} \quad (3)$$

The maximum cross correction coefficient $X_{coef}$ is used to calculate the time delay.

Time delay $t_{21}$ – Two patterns collected from different sensors or times need to be aligned first before comparison. The time delay can be found using the calculated cross-correlation below:

$$t_{21} = T\ \ when\ X_{coef}(T)\ is\ maximum \quad (4)$$

Mean Absolute Percentage Error ($MAPE$) – it is the average absolute percent error between the measured pattern and the standard pattern for each time period:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|S_{measure}(i) - S_{standard}(i)|}{S_{standard}(i)} \quad (5)$$

The *MAPE* should be calculated after the two patterns are aligned based on the Time delay $t_{21}$ and truncated to the same length *N*. Here, two bounds $MAPE_L$ and $MAPE_U$ are defined to classify the pattern based on *MAPE*. That are:

$$\begin{cases} MAPE < MAPE_L \ \rightarrow same\ pattern\ (standard) \\ MAPE_L < MAPE < MAPE_U \ \rightarrow\ distortion\ pattern\ (abnormal) \\ MAPE > MAPE_U \rightarrow different\ pattern\ or\ shift\ pattern (abnormal) \end{cases} \tag{6}$$

The two bounds $MAPE_L$ and $MAPE_U$ are determined using the $F_1$ score ($F_1$ is a measure of a test's accuracy according to the statistical theory; its range is within [0, 1]) on a cross validation dataset:

$$F_1 = 2\frac{Precison \times Recall}{Precision + Recall} \tag{7}$$

Where *Precision* is the proportion of all the positive predictions that are correct and *Recall* is proportion of all the real positive observations that are correct. They are decided using the numbers of True Positive (*TP*), False Positive (*FP*) and False Negative (*FN*) when applying $MAPE_L$ and $MAPE_U$ bounds to the cross validation dataset:

$$Precsion = \frac{TP}{TP+FP} \tag{8}$$

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

Various values of $MAPE_L$ and $MAPE_U$ are tested to identify the best bounds based on maximising the *F1* score approaching 1. When $MAPE > MAPE_U$ , a further calculation is needed to classify whether it is a different pattern or a vertical shift of the pattern. To this end, the measured signal is first determined using the following:

$$\begin{gathered} ME = \frac{1}{N}\sum_{i=1}^{N} S_{measure}(i) - S_{standard}(i) \\ S'_{measure}(i) = S_{measure}(i) - \ ME \end{gathered} \tag{10}$$

Where *ME* is the average difference between two patterns; $S'_{measure}$ is the shifted $S_{measure}$ to $S_{standard}$.

*MAPE* of $S'_{measure}$ and $S_{standard}$ is calculated again to determine the anomaly type. If $MAPE < MAPE_L$ , these two patterns are similar but shift vertically. If $ME > 0$, the pattern is shifted up, which may relate to a spindle failure or tool wear.

Based on the combination of the above statistical metrics, the types of danger signals can be identified by comparing the measured signal and standard signals based on the component modelling-ANNs. Detected danger signals could be from three aspects: (1) pattern deviations due to machine system problems, (2) pattern deviations due to the aging condition of the manufacturing system, (3) newly found patterns due to new types of machined components or from other aspects. Detailed steps for the immune process can be described below:

Immune process

1. Check if the power is close to zero during scheduled machining. If yes, send "Machine breakdown" message; otherwise, go to next step;
2. Check if the power during machining is close to the air cutting power. If yes, send a "Cutter broken" message; otherwise, go to next step;
3. Use Eq. 1 to check whether there is over-consumption or under-consumption. If yes, send a "Machine over-consumption or under-consumption" message; otherwise, go to next step;
4. Count the standby duration of power during machining against the limit of standby duration. If the limit is exceeded, send a "Machine not working" message; otherwise, go to next step;
5. Employ the component classification-ANNs to check the corresponding component of the measured pattern belongs to. If the pattern belong to the scheduled component, go to Step 7;
6. If the pattern belongs to one of the scheduled components to be machined, send an "Order modification" message and go to Step 7 for further danger signal detection; otherwise, no scheduled component is found, send a "Rush order, new pattern" message and stop;
7. Calculate the time delays $t_{21}$ of two patterns for the same components during machining (one is the standard pattern and another one is the monitored pattern). If any time shift is more than 10 seconds, send a "Timing anomaly of the control system" message; otherwise, align the two patterns using the time delay and truncate the longer pattern to the same length of the shorter pattern;
8. Calculate the $MAPE$ for the two patterns. If $MAPE_L < MAPE < MAPE_U$, send a "Distortion pattern" message; if $MAPE > MAPE_U$, go to next step;
9. Use Eq. 10 to determine whether the monitored pattern is a level shift from the standard pattern. If both the pattern during idle and machining is shifted up, send a "Spindle failure" message; if the pattern during machining is shifted up and that during idle is at the same level, send a "Tool wear" message;
10. Antibody stimulation will be triggered for the following conditions: (1) if the change of a cutter is needed and re-schedule when necessary (for tool wear), (2) maintenance of spindle by finding an alternative machine and re-schedule when necessary (spindle failure), (3) maintenance of a broken machine by identifying an alternative machine and re-schedule when necessary (machine breakdown, timing anomaly), (4) re-schedule for a rush order;
11. Antigen databases – antigen databases will be updated if new danger signals are detected and processed as abnormal conditions (e.g., on a weekly basis or based on a factory's requirements for configuration).

### 4.3 Re-scheduling optimisation

A multi-objective optimisation model and algorithm for scheduling a manufacturing process have been developed by the authors' research group (Liang et al., 2017). This optimisation model will be re-used for re-scheduling in this paper. Some definitions are given below.

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

$$E_{total}(M_i) = E_{machining}(M_i) + E_{waiting}(M_i) \quad (11)$$

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

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

$$E_{machining}(M_i) = \sum_{j=1}^{m}(A_{ij} \times E_{machining}(M_i, J_j)) \quad (12)$$

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

$$A_{ij} = \begin{cases} 1 & Component\ J_j\ is\ machined\ by\ M_i \\ 0 & Component\ J_j\ is\ not\ machined\ by\ M_i \end{cases} \quad (13)$$

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

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

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

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

$$Makespan = \underset{j=1}{\overset{n}{Max}}(T_{total}(M_i)) \quad (15)$$

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

$$\mu = \frac{\sum_{i=1}^{n} T_{total}(M_i)}{n} \quad (16)$$

$$Utlisation\_level = \sqrt{\sum_{i=1}^{n}(T_{total}(M_i) - \mu)^2} \quad (17)$$

In this research, minimisation of energy consumption, makespan and balanced utilisation level of machines are considered. As these three objective functions have very different magnitudes, normalisation of the objective functions is required. Since the maximum and minimum values of these three objective functions are unknown before optimisation, a suitable normalisation schema that normalises the objective functions in the Nadir and Utopia points has been employed (Mausser, 2006). The Utopia point $z_i^U$ provides the lower bound of the $i^{th}$ objective function and can be obtained by minimising the $i^{th}$ objective function individually, i.e.,

$$z_i^U = f_i(x^i) = min\{f_i(x)\} \quad (18)$$

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

$$z_i^N = f_i(x^k) = \max_{1 \ll j \leq I}\{f_i(x^j)\} \quad (19)$$

This normalisation 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 optimisation parameters is not very large. Hence, the energy consumption, makespan and utilisation level are to be normalised individually as:

$$\begin{cases} NE = (E_{total} - z_1^U)/(z_1^N - z_1^U) \\ NT = (Makespan - z_2^U)/(z_2^N - z_2^U) \\ NU = (Utilisation - z_3^U)/(z_3^N - z_3^U) \end{cases} \tag{20}$$

The fitness function is calculated as weighted sum of the three objectives below:

$$Fitness\text{: } min(w_1 \cdot NE + w_2 \cdot NT + w_3 \cdot NU), \quad w_1 + w_2 + w_3 = 1 \tag{21}$$

Where $w_1$, $w_2$ and $w_3$ are weights for optimisation objectives.

An evolutional optimisation algorithm, i.e., Fruit Fly Optimisation (FFO), has been developed and improved for re-scheduling optimisation. The algorithm is reported in detail in (Liang et al., 2017).

## 5. Industrial Deployment and Case Studies

### 5.1 Set-up of machining processes and energy data collection

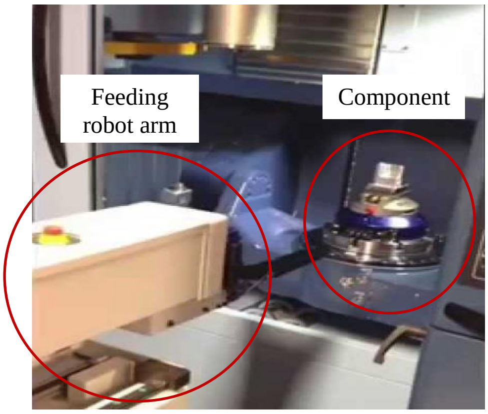
I$^2$S has been deployed in some machining companies in Sweden, U.K. and Spain (illustrated in Figure 5 and Figure 6). The deployment into a UK company (shown in Figure 6) is used here for explanation. The UK company specialises on machining high-precision components for automotive, aerospace and tooling applications. A production line, consisting of three CNC machines (MX520, Mazak VC-500A 5X and Haas VF-10) and accessory equipment, has been monitored and analysed for six months continuously to achieve energy efficient optimisation.


(a) Mazak machine (b) A component machined by Mazak (c) Energy measurement

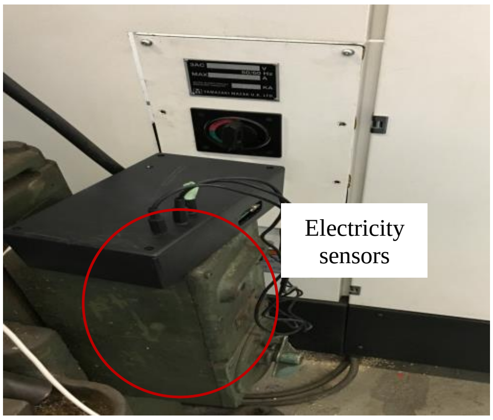
Figure 5: I$^2$S deployed into a Spanish company.

For I$^2$S, a WSN is integrated with the CNC machines as CPS. The CPS is operated through radio communication - IEEE 802.15.4 (6LoWPAN (IPv6 over Low power Wireless Personal Area Networks)) and WSN producers' own communication protocols (NXP). Three-phase current and voltage are measured by utilising current and voltage sensors. Measured data is transmitted through the 2.4 GHz Wi-Fi to a coordinator connected with an Internet-router. Energy data is stored in Hadoop for Big Data processing. For each CNC machine, the data rate of energy data for each machine is 3 readings per second. Some of the production line and monitored data are shown in Figure 6.

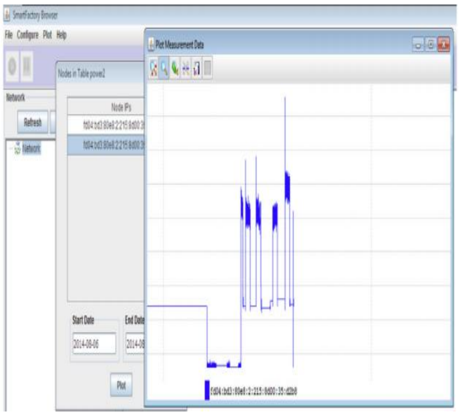

(a) Loading/unloading




(b) Loading/unloading robot




(c) Power measurement



(d) Energy measurement result

Figure 6: Energy measurement on CNC machines in a UK company.

### 5.2 Big Data partition and ANNs training

The machining process was carried out six days per week. During production, the stages include machine start-up/shut-down, idle, machining, etc. On Sunday, the machine is set either idle or shut-down. Before the deployment of I$^2$S and re-scheduling optimisation, the energy consumption for a week is shown in Figure 7. For the machining process between consecutive components, there are an unloading stage of a component that has been already machined, and a loading stage of raw materials for machining another component. The unloading/loading energy profiles are shown in Figure 8.

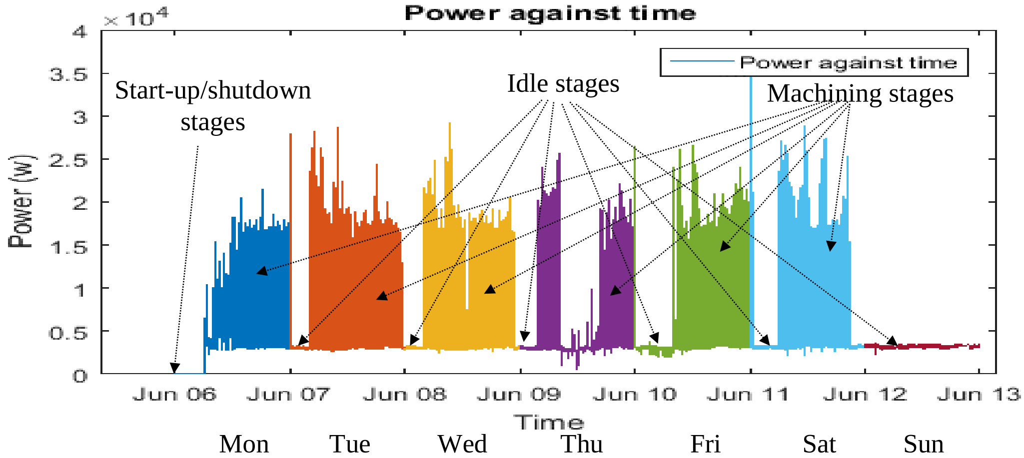



Figure 7: Energy consumption monitored for a week (before the re-scheduling optimisation of I²S).

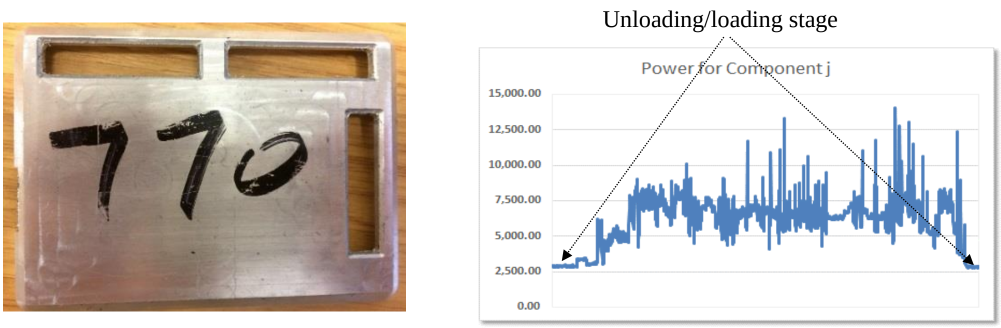



Figure 8: Energy consumption monitored during the unloading/loading stages.

In I²S, 13 types of components with total 78 energy patterns have been utilised to train the component classification-ANNs. Different structures have been used for comparison (shown in Table 3). The structure of a middle layer with 509 neurons in this layer has been finally selected due to its higher efficiency and more accuracy. The number of neurons for the input layer is 1018, and the number of neurons for the output layer is the number of component types, which is 13 in this study.

Table 3: Different middle layers and neurons for the ANNs.

| Number of middle layers | Number of neurons in middle layers | Average training time (s) | Average iterations (times) | Average accuracy (%) |
|---|---|---|---|---|
| 1 | 509 | 1.973 | 26.6 | 98.97 |
| 2 | 509 | 3.244 | 30.2 | 98.69 |
| 1 | 1018 | 4.018 | 27.6 | 97.69 |
| 2 | 1018 | 8.475 | 31 | 96.92 |
| 1 | 2036 | 6.711 | 26 | 98.46 |
| 2 | 2036 | 19.964 | 23.6 | 96.92 |
| 1 | 2037 | 7.703 | 29.2 | 98.97 |
| 2 | 2037 | 24.169 | 30.6 | 98.20 |

Figure 9 shows some results by the trained ANNs (last one is the ANNs model trained using the aligned dataset (only 3 data samples are potted here).

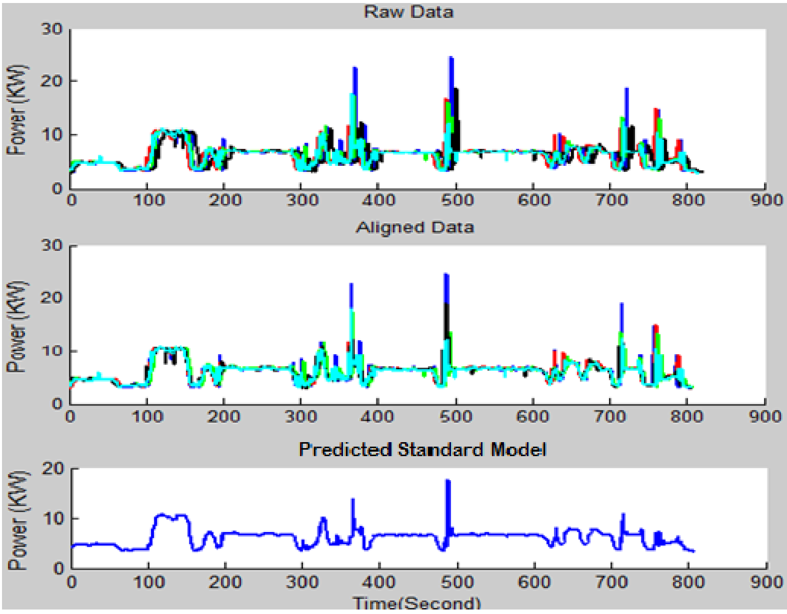



Figure 9: Training of the ANNs for identical components.

### 5.3 Immune processes

Ranges of powers for different stages were measured for individual machines (e.g., for MX520, the power for idle/loading/unloading is about 3.5-3.7 kw, for machining it is about 8.0-15 kw, for air cutting it is about 6.0-8.0 kw). There are some danger signals (potential issues) to be processed by the immune mechanism of $I^2S$. Before various danger signals are identified, the lower and upper bounds for detection of new or distortion patterns ($MAPE_L$ and $MAPE_U$) are determined by calculating the $F_1$ score and trying various values of $MAPE_L$ and $MAPE_U$ on a group of a cross validation dataset. The best ones are selected based on the $F_1$ score. In this experiment, $MAPE_L$ and $MAPE_U$ are determined as 0.09 (9%) and 0.20 (20%) respectively.

Case 1: Tool wear

Tool wear detection is illustrated in Figure 10. The machining processes for two identical components are compared. The energy consumption for the component under an ideal condition is defined as a standard pattern (in blue) and the pattern to be inspected is defined as a measured pattern (in red). In the standard pattern (in blue), its idle stage lasts from 0 to 50 seconds with a power level of 2.94KW, and the machining stage runs from 51 to 355 seconds. In the measured pattern (in red), the power level at idle stage ( 0 – 56 seconds) remains the same as that of the standard pattern. However, the machining energy increment (*MAPE*) in the machining stages for the two components is 21.8%, exceeding the pre-defined upper bound $MAPE_U$ (20%). To further determine the deviation type, the measured pattern during machining is de-trended using Eq. 10 to obtain the $S'_{measure}$. *MAPE* of

$S'_{measure}$ is calculated as +6%. It is below the pre-defined $MAPE_L$ (9%). Hence, a tool wear condition is detected.

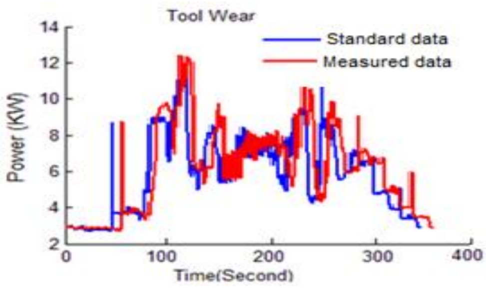


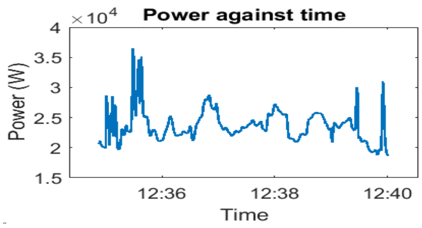

Figure 10: Energy pattern deviation due to tool wear.

Actually, the above calculation is aligned with physical experiments conducted by the authors. In the experiment, the component shown in Figure 11 has been repeatedly machined on the CNC machine for a number of times to ensure the conclusion is correct statistically. The energy consumption and surface roughness for all the machined component have been measured and compared. It is noted that when the cutter is in a severe wear condition, the energy deviation between the measured component and an identical component under a standard healthy tooling condition is 21.67%, and the corresponding average surface roughness is 1.15µm and 3.22µm respectively (shown in Figure 12). For healthy tooling conditions, the energy deviation is far below 18% and surface roughness is below 1.15µm. The threshold (18%) obtained using the experiments is very close to $MAPE_U$ (20%) that is optimised based on the $F_1$ score. Therefore, the approach is validated through the experiments.

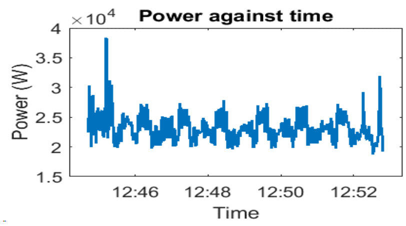
(a) Component under a standard condition


(b) Component under an abnormal condition

Figure 11: A component is machined under standard and abnormal conditions.




(a) Power profile under a standard condition




(b) Power profile under an abnormal condition

Figure 12: Energy profiles for machining identified components under standard/abnormal conditions (energy consumptions are 2.03Kwh and 2.47Kwh respectively - deviation is 21.67%).

Case 2: Timing anomaly

For timing anomaly, the pattern difference is shown in Figure 13. An unexpected time delay of 35 seconds at No. 480 seconds in the standard pattern and No. 505 seconds in the measured pattern is detected. Such long-time shift is more than timing anomaly threshold so that it could indicate a possible timing anomaly.

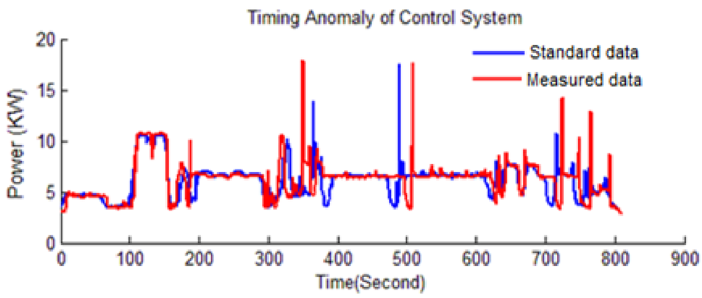



Figure 13: Energy pattern deviation due to timing anomaly.

Case 3: No working

No working will generate long standby as shown in Figure 14. The measured power is around the standby power (3.6KW for the machine used in this case) for a very long period (as defined previously, if the standby time exceeds 60 seconds, a warning message would be sent out). It indicates the machine is not working. It is found out that the machine door was not closed properly so that the machine was not running.

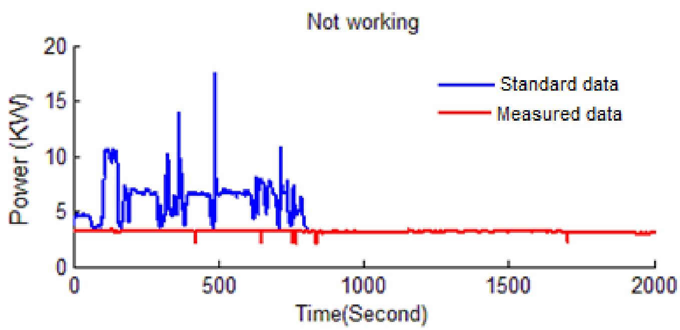



Figure 14: Energy pattern deviation due to a non-working condition.

Case 4: Cutter broken

The situation is illustrated in Figure 15. It starts from the No. 214 seconds (the spike in red line), and followed by the power level (3.9kW) that is close to the standby level (3.6kW). It is judged the cutter was broken from No. 214 seconds.

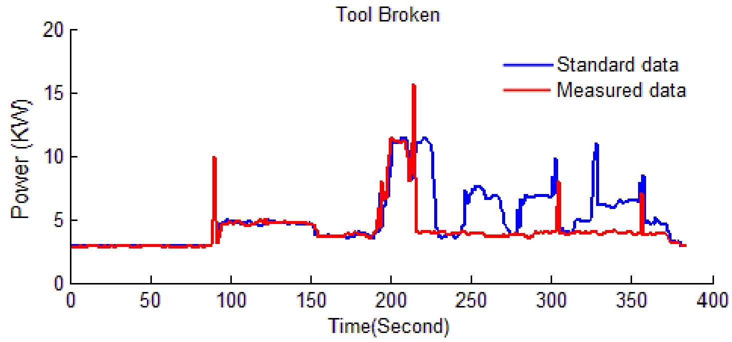



Figure 15: Energy pattern deviation due to a broken cutter.

Case 5: Spindle failure

For this abnormal condition, an unexpected energy spike without change in the spindle speed followed by increased energy during idle and machining are detected (shown in Figure 16).

In the standard pattern (in blue line), the idle stage lasts from No. 381 to No. 470 seconds at a power level of 3.6KW. The machining stage lasts from No. 471 to No. 760 seconds. In the measured data pattern (in red line), an unexpected energy spike is detected in No. 351 second and the following energy during idle and machining shifts up at levels of 21.5% and 20.3% respectively. They exceed the pre-defined threshold 20%. As thus, the measured data is de-trended using Eq. 10 and *MAPE* of the de-trended dataset is +4.3% (which is below the pre-defined $MAPE_L$ (9%)). As thus, a spindle failure condition is detected.

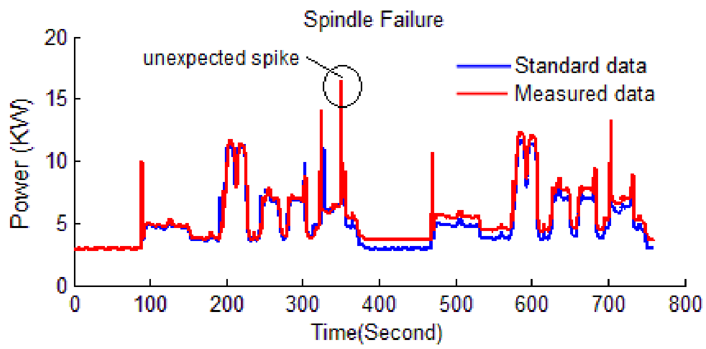



Figure 16: Energy pattern deviation due to a spindle failure condition.

Case 6: New patterns

It is judged that the signal in Figure 17 is a new component for machining. No any abnormal conditions are detected in these patterns. As thus they are recorded as normal patterns and will not be handled as a danger signal. The newly generated patterns for machining new components are updated into the training set of the component classification-ANNs. Danger signals shown in Figure 18 and Figure 19 are new signals and will be reported to maintenance engineers. If judged as abnormal, they will be processed and recorded into the antigen databases.

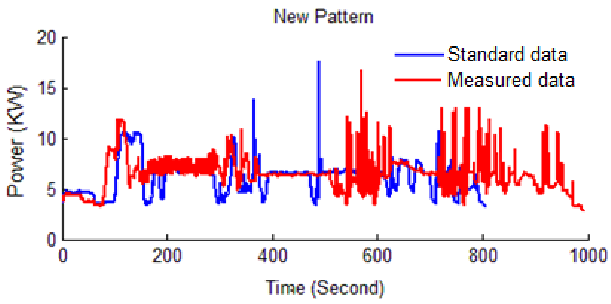



Figure 17: A new energy consumption pattern for a newly machined component.

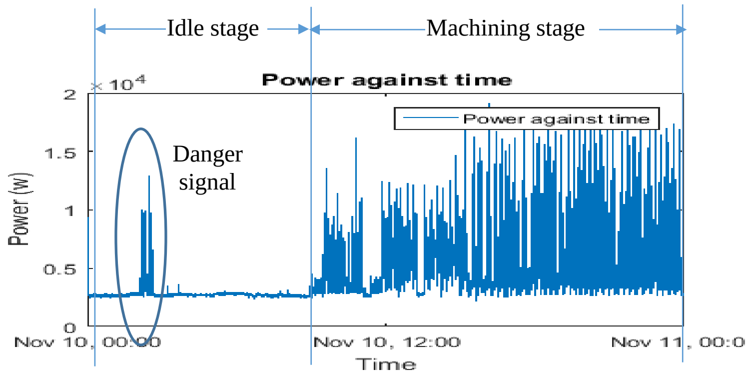



Figure 18: A danger signal.

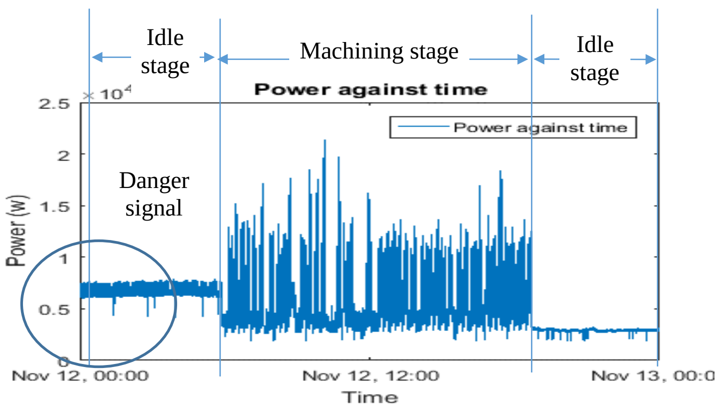


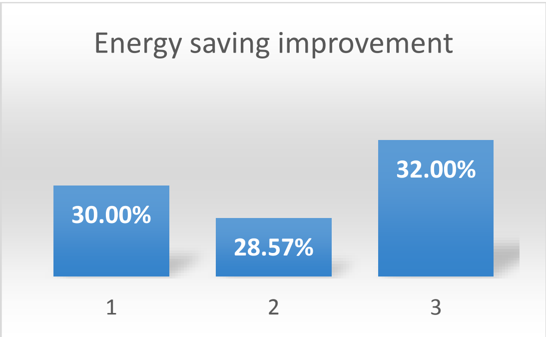

Figure 19: Another danger signal.

System condition evolving

The thresholds of machines are adjusted based on experiments to be adaptive to the machine aging conditions. The relevant thresholds should be set based on longer term experiments (the research work is ongoing).

Re-scheduling due to the breakdown of a machine

Figure 7 shows one week production before the deployment of $I^2S$ into the factory. Due to the unexpected breakdown of the Mazak machine, the productivity on Thursday was almost 50% less than other days. Via I²S, the Mazak machine was identified for maintenance so that the components arranged for the Mazak need to be shifted to the other two machines, i.e., MX520 and Haas. Meanwhile, it was identified that there are more issues like door stuck, insufficient raw material supply during the early morning so there were no many machining activities during the periods. Measurements were introduced to enable the automatic lines to keep continuous execution during the early mornings as well. Re-scheduling optimisation made improvements for energy saving and productivity (three-month improvement in the factory is shown in Figure 20).



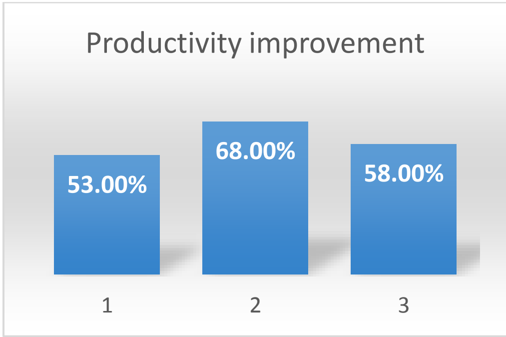



Figure 20: Improvements for three months by using I²S into the production line.

## 5. Conclusions

In this paper, an innovative I²S has been developed for energy efficient manufacturing monitoring, analysis and optimisation. The system is enabled by effective Big Data analytics and intelligent immune mechanisms to adapt to condition changes of machining processes. A re-scheduling algorithm is triggered when necessary thereby achieving multi-objective optimisation of energy consumption and manufacturing performance. The innovations and characteristics of I²S include:

- By integrating with CPS, ANNs and re-scheduling optimisation, an innovative immune mechanism has been designed to effectively process energy Big Data to achieve energy efficient optimisation for manufacturing lifecycles;
- I²S has been deployed into some European factories for trials for months. Real-world case studies have been used for system validation. For the companies, around 30% energy saving and over 50% productivity improvement have been achieved. The effective applicability of I²S to industrial environments has been proved. By using I²S, sustainability improvements on the environmental, economic and social aspects have been achieved (environmental and economic - energy efficient manufacturing, less unexpected breaks to improve energy efficiency and productivity, social - intelligent monitoring and processing to avoid tedious human intervention and errors as a more user - friendly working environment).

There are ongoing research to improve I²S further. Near future research issues include:

- In practices, the error of measured data could be a very significant issue. Measures to eliminate the error effect are under investigation. Longer-term experiments will be carried out to establish more reliable thresholds of machine aging. Meanwhile, optimisation approaches are under research to define the lower and upper energy bounds of machined components.

- Investigations on integrating the immune mechanism and edge computing (a new IT infrastructure) are carried out to improve the efficiency and effectiveness of $I^2S$ for industrial applications.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**Nomenclature:**

| | |
|---|---|
| $E_{\text{waiting}}(M_i)$ | The energy consumption of Machine $M_i$ during waiting |
| $E_{machining}(M_i, J_j)$ | The energy consumption of machining Component $J_j$ by Machine $M_i$ |
| $E_{machining}(M_i)$ | The energy consumption of Machine $M_i$ during machining |
| $E_{total}(M_i)$ | The energy consumed during all the phases of Machine $M_i$ |
| $F_1$ | A measure of a test's accuracy |
| *FN* | False Negative |
| *FP* | False Positive |
| *M* | The total number of components to be machined |
| *MAPE* | Mean Absolute Percentage Error |
| $MAPE_L$, $MAPE_U$ | Lower bound and upper bound of Mean Absolute Percentage Error |
| *ME* | The Mean Error between two patterns |
| *N* | The bigger number of the samples of the two patterns |
| $N_1$ | The total number of the measured power points in $S_{measure}$ |
| $P_L$, $P_U$ | Lower bound and upper bound of a standard energy pattern |
| *Precision* | The proportion of all the positive predictions that are correct |
| *Recall* | Proportion of all the real positive observations that are correct |
| $S_{measure}$ | Measured energy pattern for machining a component |
| $S_{standard}$, | Standard energy pattern for machining a component |
| $S'_{measure}$ | The shifted $S_{measure}$ to $S_{standard}$ |
| $t_{21}$ | Time delay |
| *TP* | True Positive |
| $X_{coef}$ | Cross-correction coefficient |
| $z_i^N$ | The upper bound of the $i^{th}$ objective function |
| $z_i^U$ | The lower bound of the $i^{th}$ objective function |
| $\mu_{measure}$, $\mu_{standard}$ | The means of time patterns |
| $\sigma_{Smeasure,Sstandard}$ | The cross-covariance between the pair of patterns |