An energy data-driven decision support system for high-performance manufacturing industries

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Abstract: To maintain high performance in the looming economic recession, manufacturers are looking for ways to reduce plant downtime, maximise asset utilisation, and improve energy efficiency. In this paper, a unified decision support system (DSS) is proposed, which uses real-time energy measurements and process operational states to make effective decisions, enabling high-performance manufacturing. To reduce the number of required sensors and amount of logged data, our proposed DSS includes an intelligent framework which identifies the process operational states based on energy measurements. This process identification framework uses Haar transform and empirical Bayesian (EBayes) threshold to segment the power data and support vector machines (SVMs) to cluster the power segments into groups according to the underlying process operational states. To justify our proposed framework, comparative experiments with an existing framework are evaluated on two industrial applications, an injection moulding system and a stamping system. Experiment results show that our proposed framework is more effective in identifying the process operational states using the energy patterns.

Keywords: decision support system; DSS; discrete wavelet transform; energy-efficient manufacturing; support vector machine; SVM.


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1 Introduction

Manufacturers today face a competitive, volatile, and fast-paced business environment. A variety of factors have adjusted the manufacturing business in recent years. The most prominent factor has been the movement from a period of high demand for commodities, which led to tremendous growth in revenues and profits for many companies, to a looming global economic recession and consumer slump in demand (Koren, 2010; Gomes et al., 2004). To stay competitive, manufacturers are forced to improve the effectiveness and efficiencies of their manufacturing systems to deliver a higher variety of products with shorter life cycles in a shorter period of time. Manufacturers have pursued a range of new approaches, from agile manufacturing to collaborative manufacturing and supply chain management. While few have succeeded, many have failed (National Association of Manufacturers, 2005).

In current economic situation, manufacturers are considering high-performance manufacturing in terms of improving equipment’s reliability and preventing plant downtime (Kothamasu et al., 2006), driving higher asset utilisation and cost effectiveness (ElMaraghy, 2005), and most importantly, transforming towards energy-efficient manufacturing through process design and optimisation (Le et al., 2012). Furthermore, customers nowadays expect manufactured products to be not only free of flaws but also environmentally sustainable, which often requires manufacturers to report a full life-cycle analysis to assess cradle-to-grave environmental impacts associated with a product (Tanaka, 2011). As such, high-performance manufacturing is becoming one of the greatest strategic challenges and opportunities for manufacturing industries, not only from an engineering perspective, but also from a marketing and sales perspective.

The first step towards high-performance manufacturing requires a unified decision support system (DSS) to align real-time feedback data from manufacturing shop floors more closely with business and production requirements, and hence dynamically optimise different key performance indicators across the enterprise (Parsaei et al., 1996; Michalewicz et al., 2005; Liu et al., 2011). In this view, a manufacturing work cell can no longer work in silos within shop floors, but rather as an integral part. Sensory data need not to be consolidated manually and locally, but must be shared and synchronised across the company, resulting in a sheer variety and volume of data. In many large-scale information and realistic engineering systems, data is usually logged and collected from the various sources of systems and sensors at a fixed sampling rate in a big data matrix. This impedes the effectiveness of a DSS in extracting useful information and features from a data matrix for making effective decisions (Pang et al., 2011). DSS is an information system which supports decision-making processes and problem-solving activities. As a concept, DSS has been proliferated and evolved over the past few decades (Eom et al., 1998). With advancing information and communications technology, DSS is nowadays widely implemented in global industries. Most existing DSS architectures are highly specific, which focus to solve one particular problem, such as supplier selection (Chou and Chang, 2008), reconfiguration product design (Kristianto et al., 2011), and machine selection (Tabucanon et al., 1994), etc.

In this paper, we provide a unified DSS architecture. Using real-time energy measurements and process operational states, our proposed DSS aims to make energy-efficient, cost-effective, and reliable decisions for the next generation of
high-performance manufacturing. In addition, life-cycle analysis can be partially supported, as energy consumption during the production stage of a product’s life-cycle is accurately logged and documented. To reduce the number of required sensors and amount of logged data, our proposed DSS includes an intelligent framework which identifies the process operational states based on energy measurements. This process identification framework uses Haar transform and empirical Bayesian (EBayes) threshold to segment the power data and support vector machines (SVMs) to cluster the power segments into groups according to the underlying process operational states. To justify our proposed framework, comparative experiments with an existing framework (Chee et al., 2011) are evaluated on two industrial applications, an injection moulding system and a stamping system. Experiment results show that our proposed framework is more effective in identifying process operational states using energy patterns.

The rest of this paper is organised as follows. Section 2 describes the DSS architecture. Section 3 proposes the process identification framework, while Section 4 presents two industrial applications with experiment results. Section 5 discusses the development and implementation of effective models for making energy-efficient, cost-effective, and reliable decisions. Finally, our conclusion and future work directions are summarised in Section 6.

2 Decision support system

In this section, a generic and unified DSS is proposed enabling high-performance manufacturing. In general, there is no universally accepted taxonomy of DSS models as different researchers propose different classifications. Herein, we follow (Parsaei et al., 1996) to discuss three generic approaches to develop a DSS.

- Data-driven DSS. A data-driven DSS emphasises on access to and manipulation of a data logged from various sources of sensors and metres. Data analytic and artificial intelligent techniques can be used for decision-making model.

- Knowledge-based DSS. A knowledge-based DSS provides specialised problem solving expertise stored as facts, rules, procedures, etc. Knowledge-driven DSS is developed based on engineering and management expertise and experiences.

- Model-based DSS. A model-based DSS uses data and parameters provided by users to assist decision makers in analysing a situation. Model-driven DSS can be built using various statistical, optimisation, or simulation models in current literature.

The developed DSS must be able for the extraction and mash-up of heterogeneous data using artificial intelligence and data-mining principles to combine the data and human expertise in creating new services, experiences, decisions, and maintenance rule-bases, etc. It must also integrate data from different sources and formats seamlessly using a data-aware correlation engine, making existing data more powerful for technical and professional users with a more potent decision-making and predictive capability. The architecture of our proposed DSS is shown in Figure 1.
In today’s information technology era, the amount of digital, sensory, imagery, and audio data, etc., from various sources such as simulation systems, control systems, inspection processes, etc., is expanding at an explosive rate. As such, the proposed DSS architecture must include a centralised and distributed monitoring network to enable the holistic access and analysis of a large variety of data from manufacturing shop floors at different locations. The monitoring network often comprises of various types of metres and sensors. At the shop-floor level, the local monitoring systems communicate via internal buses. The shop-floor monitoring systems are interfaced to the DSS over a communication platform, which includes two bus systems, namely data bus and fault tolerant control (FTC) bus, respectively. The key advantage of such distributed bus network is the reduction of required bus cables and wires. Although computer networking protocols such as Ethernet for local area networks and transmission control protocol/internet protocol for the internet are most suitable for the data bus, industrial computer network protocols (e.g., Fieldbus) and vehicle bus protocols (e.g., controller area network bus and local interconnect network bus) can also be applied (Bradley et al., 1991). In addition, other data transmission equipments such as data acquisition systems and transducers may also be required. From the data bus, heterogeneous data are aggregated, processed (if necessary), and stored. FTC bus is highly important for our proposed DSS architecture to prevent unpredicted downtime due to machinery failures. FTC data could be in various forms such as vibrational, acoustic, and force data, etc., depending on specific systems and applications. Various FTC schemes in current
literature can be applied, one popular FTC scheme is the fault detection and isolation based on analytical redundancy (De Silva, 1989).

The next important task is to provide effective monitoring of manufacturing process’s operational states. This task is accomplished by an intelligent process identification framework, whose mathematical rigour will be detailed in Section 3. Real-time process operational states, energy measurements, and other related data (if any) are collated and synthesised to indicate the amount of energy consumption during specific process operational states. This encompasses not only the amount of energy required to run industrial machines, but would possibly include other facilities’ energy consumption such as lighting, heating, ventilation, and air conditioning, etc., which can contribute as much as 30% of the total energy consumption in a shop floor. A popular energy model in current literature to analyse manufacturing processes and facilities is the state-based model, where the entire process cycle is divided into a finite number of discrete operational states (Vijayaraghavan and Dornfeld, 2010; Weinert et al., 2011). Such energy model is based on integrated measurements over time to determine time-based power consumption in accordance with the underlying operational states, for example, the amount of energy being consumed during production state versus the amount of energy being consumed when the resource is in idle state.

The obtained process operational states and energy measurements are then fed into several useful decision-making models. In addition, other production and business requirements such as electricity prices, raw material prices, operational expenditure (OPEX), and capital expenditure (CAPEX), etc., may also be required. The objective of decision-making models is to make energy-efficient, cost-effective, reliable decisions for high-performance manufacturing. The contents of decision-making models will be detailed in Section 5.

3 Process identification framework

In this section, an intelligent framework for identification of process operational states based on power data is proposed. Structurally, our proposed framework consists of two consecutive layers as shown in Figure 1. The first layer uses Haar transform and an EBayes threshold to segregate the power data into segments. The second layer includes feature extraction and a two-stage SVM to sort the data segments into clusters, each cluster indicates an operational state.

3.1 Signal segmentation

To segment the power data, Haar transform is first used to compute the wavelet coefficients. The computed wavelet coefficients are then passed through an EBayes threshold level, where the cross-over coefficients indicate the change points of process operational states.

Haar transform can be interpreted as a dyadic multi-rate filter bank. It uses both scaling functions and wavelet functions, which are associated with the low-pass and high-pass filters, respectively. The scaling function generates approximation coefficients, while wavelet function computes detail coefficients. Wavelet transforms are recursive,
where wavelet coefficients computed in previous iteration are inputs for subsequent iteration. A non-overlapping rectangular window is used to sample the data, where the window width is two for the initial iteration and is doubled at each subsequent iteration during wavelet decomposition.

Consider a power data \( p = \{ p_i : i \in \mathbb{Z}^+ \} \). Let us also denote the wavelet approximation and detail coefficients by \( a = \{ a_i : i \in \mathbb{Z}^+ \} \) and \( d = \{ d_i : i \in \mathbb{Z}^+ \} \), respectively. As such, the Haar transform of \( p \) is computed as follows (Burrus et al., 1998)

\[
a_i = \frac{p_i + p_{i+1}}{\sqrt{2}},
\]

\[
d_i = \frac{p_i - p_{i+1}}{\sqrt{2}}.
\]

In our industrial applications, a level-five wavelet decomposition is used, as it provides sufficient wavelet resolution to detect significant change points in the power data. Obviously, a higher-level wavelet decomposition provides better results, but also requires more computational efforts.

In data segmentation using wavelet transforms, selecting an appropriate threshold method is crucial. An unnecessarily large threshold will segregate too many coefficients resulting in over-segmentation, and vice versa. Recently, an empirical EBayes threshold for wavelet decomposition has been proposed in Johnstone and Silverman (2005), which was proven to outperform existing threshold methods for different datasets, e.g., the modified universal threshold, the sureshrink and false discovery rate techniques, and the block thresholdings such as neighBlock or neighCoeK (Alsaidi and Altaher, 2010; Fryzlewicz, 2007).

Consider the wavelet coefficients \( d = \{ d_i : i \in \mathbb{Z}^+ \} \) inundated with noise \( \varepsilon \) which can be written as

\[
d_i = \mu_i + \varepsilon_i,
\]

where \( \mu \) is the distribution mean. As such, finding a threshold value using EBayes includes three main steps.

**Step 1** The parameters \( \mu \) are modelled as having independent prior distributions \( f_{\text{prior}} \) each given by

\[
f_{\text{prior}}(\mu) = (1 - w) \delta_0(\mu) + w\sigma(\mu),
\]

where \( w, 0 < w < 1 \), is a probabilistic variable. \( \delta_0 \) is the Dirac function, and \( \sigma \) is a symmetric heavy-tailed density such Laplace or Cauchy density.

**Step 2** The probability \( w \) is estimated by defining the marginal maximum likelihood estimator \( \hat{w} \) of \( w \) to be the maximiser of marginal log-likelihood as follows:

\[
\hat{w} = \arg \max_w \sum_{i=1}^m \log \left\{ (1 - w)\phi(d_i) + w\phi(d_i) \right\},
\]
where \( g = \sigma \ast \phi \), and \( \ast \) denotes convolution. \( m \) denotes the length of data. To avoid confusion with the scaling function of wavelet families, \( \phi \) is used to denote the standard normal density.

Step 3 An estimation for \( \mu \) is found by substituting \( \hat{w} \) back into (4) and taking the posterior median of \( \mu \).

3.2 Segment clustering

One now wishes to extract useful features from the obtained power segments. To effectively eliminate outliers, which apparently correspond to the segments with many sharp transitional spikes, the mean absolute deviation (MAD) is used. Consider a data segment \( p = \{ p_i : i \in \mathbb{Z}^+ \} \), MAD is defined as the median of absolute deviations from the segment’s median described by:

\[
\text{MAD}(p) = \text{median}_{i} \left( |p_i - \text{median}_{j} (p_j)| \right). \tag{6}
\]

Next, the geometric median (GM) is computed to measure the central tendency of power segments. Our purpose is to determine the amplitude level, which is relatively constant after removing outliers. GM is used instead of the mean, because the power segments possibly contain abnormal nadirs at both ends. Formally, the GM of a power segment \( p \) is computed by:

\[
\text{GM}(p) = \arg \min_{y} \sum_{i=1}^{m} \|p_i - y\|. \tag{7}
\]

To explore the dynamic characteristics of power segments, third-order auto regression (AR) features are used. A third-order AR model of a power segments \( p \) is defined by:

\[
p_t = \omega + \sum_{i=1}^{n} \beta_i p_{t-i} + \varsigma, \tag{8}
\]

where \( \beta_i \) denotes the regression coefficient, \( \omega \) is the intercept variable, and \( \varsigma \) is a noise parameter. \( \beta, \omega, \) and \( \varsigma \) can be estimated by various step-wise least-squares algorithms. Two algorithms, the Levinson-Durbin and Burg algorithms, are widely used to estimate the coefficients of a AR model (Neumaier and Schneider, 2001; Schneider and Neumaier, 2001). An exact value of \( n \) for a given power segment is not known \( \text{a priori} \); it is desirable to reduce the computational complexity by choosing the minimal \( n \) such that the AR model is of satisfactory performance. In our industrial applications, \( n = 3 \) is chosen as it provides a sufficient fit to the power segments. As a result, three AR features \( \beta_1, \beta_2, \) and \( \beta_3 \) are obtained. In summary, a total of five features has been extracted for segment clustering including MAD, GM, \( \beta_1, \beta_2, \) and \( \beta_3 \).

Once features are extracted, each power segment is now represented by a feature vector \( x \in \mathbb{R}^5 \) with element \( x_j \) denotes the \( j \)-th feature. To ensure the segment clustering is of satisfactory accuracy, the first-stage SVM – an one-class SVM – is designated to eliminate outliers from the set of power segments. In a statistical sense, an outlier is defined as an observation which is numerically distant from the rest of the data. The second-stage SVM – a multi-class SVM – is used to cluster the remaining power
segments into groups, each of which indicates an operational state. It is worth noting that the first-stage SVM indeed solves an unsupervised learning problem as the labels of segments from ‘outlier’ cluster and ‘non-outlier’ clusters are not known a priori. On the contrary, the second-stage SVM deals with a supervised learning problem where the labels of all power segments are available. The whole set of power segments is segregated into ‘training’ set and ‘validation’ set – the former used to train the underlying clustering mechanism, and the latter used to test if the trained SVMs are of satisfactory accuracy.

SVM is a well-known classification method which has been applied to various engineering applications (Steinwart and Christmann, 2008). Its objective is to find a separating hyperplane for which the distance between clusters, measured along a line perpendicular to the hyperplane, is maximised. This can be achieved by solving the following constrained optimisation problem:

\[
\begin{align*}
\min_{w,b,\alpha,\xi} & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{D} \xi_i, \\
\text{s.t.,} & \quad y_i(w \cdot x_i - b) \geq 1 - \xi_i, \xi_i \geq 0, \forall i = 1, ..., D,
\end{align*}
\]

where vector \( w \) determines the orientation of the hyperplane, and \( \xi_i \leq 0 \) are slack variables. \( C \) denotes a positive constant which specifies the trade-off between margin and misclassification error, and \( D \) denotes the number of power segments.

For a non-linear decision surface, this optimisation problem can be addressed by the concept of using kernel function \( k \). Their decision function has the following form:

\[
y(x) = \sum_{i=1}^{N_s} \alpha_i k(x, x_i) + b,
\]

where \( k(\cdot, \cdot) \) represents the kernel, which can be shown to compute the dot products in associated feature space \( \mathbb{R}^s \), i.e., \( k(x, x') = \langle \Phi(x), \Phi(x') \rangle \). The function \( \Phi : x \in \mathbb{R}^s \rightarrow \Phi(x) \) maps the feature vectors into kernel space. The SVM decision hyperplane is determined by \( \psi = \sum_{i=1}^{N_s} \alpha_i \Phi(x_i) \), with \( N_s \) support vectors \( x_i \) and non-vanishing coefficients \( \alpha_i \). In this paper, the most common type of kernel, the radial basis function (RBF), is used where \( k(x, x') = \exp(-\gamma \|x - x'\|^2) \). The RBF kernel is often designed by tuning the kernel parameter pair \( (C, \gamma) \) using cross-validation method (Schölkopf et al., 2011). It is worth noting that cross-validation method can not be used to train the SVM in the case of unsupervised learning problem due to the lack of segment labels. In this case, the kernel parameter pair \( (C, \gamma) \) is obtained by an iterative method (Manevitz and Yousef, 2002).

4 Industrial applications

The performance of our proposed process identification framework is evaluated on two industrial applications. In the first application, energy consumption of two industrial injection moulding machines is investigated, namely, Arburg A220 S 150-60 and Arburg
A420 S 1000-150, respectively. In the second application, eight stamping machines at one stamping company in the Republic of Singapore are studied. The stamping machines are only denoted by M1-M8 due to confidential restrictions.

4.1 Experiment setup

In both industrial applications, three-phase electrical parameters are continually measured using Rudolf R-DPA96A digital power analysers (RUDOLFs). In our experiments, only real power is used, but other electric variables such as reactive power, apparent power, and power factor, etc., are all measured. To interface RUDOLFs with computers or handled devices, a graphic user interface (GUI) has been developed in LabVIEW©. The sampling frequency of RUDOLFs is set to 1 Hz. Energy consumption produced by manufacturing 17 injection moulding parts and ten stamping parts are logged. Each part is manufactured massively, i.e., numerous workpieces are produced.

4.1.1 Injection moulding process

Injection moulding is a typical manufacturing process for producing parts from plastic materials. Materials are fed into a heated barrel, mixed, and forced into a mould cavity, where they are cooled and hardened to the shape of the cavity. The entire injection moulding cycle can be segregated into six operational states including switch off, warm up, idle, pump/heat, start up, and moulding. Interested readers are referred to Le et al. (2012) for more descriptions of these operational states.

4.1.2 Stamping process

Stamping process includes several operations of modifying raw materials, e.g., punching, coining, blanking, piercing, and bending, etc. Eight studied stamping machines are operating at different conditions (e.g., age, utilisation, maintenance frequency). Their performances and efficiencies are given in Table 1. There is a wide range in average stamping power (even for different machines of the same model). This is due to a multitude of real-time events, e.g., tooling, machine loading, machine degradation, machine age, and tool degradation, etc., which are not predictable. In our experiments, the inputs to stamping machines are raw metal sheets, while manufactured products are various types of voice coil motor yokes used in commercial hard disk drives’ actuators.

Table 1  Stamping machines performance and efficiency

<table>
<thead>
<tr>
<th>Machine ID</th>
<th>Rated tonnage (tonnes)</th>
<th>Rated power (kW)</th>
<th>Actual max load (tonnes)</th>
<th>Average power (kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>200</td>
<td>22</td>
<td>168</td>
<td>6.67</td>
</tr>
<tr>
<td>M2</td>
<td>300</td>
<td>37</td>
<td>238</td>
<td>6.45</td>
</tr>
<tr>
<td>M3</td>
<td>300</td>
<td>37</td>
<td>250</td>
<td>7.60</td>
</tr>
<tr>
<td>M4</td>
<td>300</td>
<td>37</td>
<td>183</td>
<td>6.19</td>
</tr>
<tr>
<td>M5</td>
<td>300</td>
<td>37</td>
<td>176</td>
<td>5.37</td>
</tr>
<tr>
<td>M6</td>
<td>300</td>
<td>37</td>
<td>198</td>
<td>6.46</td>
</tr>
<tr>
<td>M7</td>
<td>300</td>
<td>37</td>
<td>202</td>
<td>7.79</td>
</tr>
<tr>
<td>M8</td>
<td>300</td>
<td>37</td>
<td>-</td>
<td>12.23</td>
</tr>
</tbody>
</table>
The entire stamping cycle can be divided into five operational states, namely, switch off, warm up, idle, start up, and stamping. Energy consumption of the first four states are relatively similar to injection moulding process. The stamping state specially includes many spikes. Each spike is observed every time the stamping press moves down to perform stamping operations. Among the stamping machines, M8 is oldest and has relatively different patterns in power data. Thus, all power segments extracted from M8 are labelled as abnormal state. An illustrated comparison between segments from stamping and abnormal states is shown in Figure 2, where different patterns can be clearly observed.

4.2 Experiment results

In this section, the performance of our proposed framework is compared with an existing framework reported by Chee et al. (2011). It is worth noting that there are two main differences between the two frameworks. First, our proposed framework does not include
the Savitzky-Golay (SG) filter for pre-processing energy measurements and the EBayes threshold is used instead of the universal threshold. Second, SVM is used to cluster the power segments instead of the fuzzy c-means (FCM) algorithm.

**Figure 3** The discrete-state power data of industrial processes, (a) injection moulding and (b) stamping

Examples of power data of injection moulding process and stamping process are shown in Figure 3, where the process operational states are clearly distinguished in different colours. It can be seen that each operational state exhibits a relatively distinct level of magnitude in the power data. Both process identification frameworks are implemented in MATLAB®. The power data of both datasets are segmented as discussed. An example of the signal segmentation using our proposed framework on a power data from Arburg 220S is shown in Figure 4. It can be seen that the power data is first transformed into wavelet coefficients. Wavelet coefficients are then filtered by an EBayes threshold (the dashed line), where only cross-over coefficients are accentuated indicating the change points of process operational states.
Figure 4  An illustrated example of signal segmentation using the our proposed framework, (a) power data (b) wavelet coefficients with EBayes threshold (dashed line), and (c) detected change points.

Figure 5  An example of outlier detection of moulding state.
Five useful features including the MAD, GM, and three AR parameters are extracted from each power segment. The first-stage SVM is now used to detect ‘outlier’ power segments. For illustration, an example of detected ‘outlier’ segments in moulding state is shown in Figure 5. The outlier detection results is reported in Table 2. The best SVM kernel parameters \( \gamma = 0.71 \) and \( \gamma = 0.96 \) are obtained for the injection and stamping datasets, respectively.

**Table 2**  
Outlier detection results using our proposed framework

<table>
<thead>
<tr>
<th>Dataset</th>
<th>SVM kernel parameter ( \gamma )</th>
<th>Percentage of outlier segments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Injection</td>
<td>0.71</td>
<td>6.4%</td>
</tr>
<tr>
<td>Stamping</td>
<td>0.96</td>
<td>12.23%</td>
</tr>
</tbody>
</table>

4.2.1 Identification results with sufficient training data

We now wish to cluster the remaining power segments according to their underlying process operational states. In this section, the clustering performance of both frameworks are evaluated with sufficient training data, where both datasets are segregated into 50% for training and 50% for testing. For convenience, the operational states of both injection moulding and stamping processes are numerically labelled in Table 3.

**Table 3**  
Cluster label for injection moulding and stamping operational states

<table>
<thead>
<tr>
<th>Injection dataset cluster label</th>
<th>Operational state</th>
<th>Stamping dataset cluster label</th>
<th>Operational state</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Switch off</td>
<td>1</td>
<td>Switch off</td>
</tr>
<tr>
<td>2</td>
<td>Warm up</td>
<td>2</td>
<td>Warm up</td>
</tr>
<tr>
<td>3</td>
<td>Idle</td>
<td>3</td>
<td>Idle</td>
</tr>
<tr>
<td>4</td>
<td>Start up</td>
<td>4</td>
<td>Start up</td>
</tr>
<tr>
<td>5</td>
<td>Pump/heat</td>
<td>5</td>
<td>Stamping</td>
</tr>
<tr>
<td>6</td>
<td>Moulding</td>
<td>6</td>
<td>Abnormal</td>
</tr>
</tbody>
</table>

To tune the parameter pair \((C, \gamma)\) of the second-stage SVM, a coarse grid-search is first performed using cross-validation method. Various pairs of \((C, \gamma)\) values are tested and the one with the best cross-validation accuracy is picked. An exponentially growing sequence of \((C, \gamma)\) is examined, e.g., \(C = (2^{-4}, 2^{-3}, \ldots, 2^{15})\) and \(\gamma = (2^{-14}, 2^{-13}, \ldots, 2^{5})\). Our results show that the best \((C, \gamma)\) for injection and stamping datasets are \((2^5; 2^{-5})\) and \((2^4; 2^{-3})\) with the corresponding cross-validation rate are 84% and 79.5%, respectively. Thus, finer grid searches on the neighbourhood of \((2^5; 2^{-5})\) and \((2^4; 2^{-3})\) are conducted. Better cross-validation rates 84.699% at \((2^{4.77}; 2^{-4.51})\) and 80.300% at \((2^{4.48}; 2^{-2.78})\) are obtained for injection and stamping datasets, respectively.

The validation results using the proposed framework for identification of the operational states are reported in Table 4. For injection dataset, our proposed framework classifies 467 out of 474 different segments correctly, thereby yielding an accuracy of 98.52% in identification of the operational states. For the stamping dataset, 352 out of 358 segments are identified correctly with an accuracy of 98.32%. In particular, it can be seen from Table 4 that the proposed method is able to classify switch off, idle and warm up states very accurately. This is because the energy consumption of these two states are
completely or almost flat with few fluctuations. Minor classification errors occur for the start up state, as its energy consumption patterns is similar to warm up state both having sharp increases from low levels in power data. It can also be seen that most error cases arise from erroneous classification of the moulding state (a prediction error of 3.22%) due to the many different sub-states. There is also a prediction error of 6.25% in abnormal state, because some power segments in switch off and idle states of M8 are similar to other machines. The proposed framework accurately classifies segments from stamping, start up, and warm up states of M8 as abnormal segments. With the same experiment setups, the existing framework yields an accuracy of 97.08% and 96.68% in identification of the process operational states for the injection moulding and stamping datasets, respectively. It can be seen that our proposed framework slightly outperforms in the case of sufficient training data.

<table>
<thead>
<tr>
<th>Table 4</th>
<th>Number of validated segments using our proposed process identification framework with sufficient training data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Injection dataset cluster</td>
<td>Correct</td>
</tr>
<tr>
<td>1</td>
<td>72</td>
</tr>
<tr>
<td>2</td>
<td>36</td>
</tr>
<tr>
<td>3</td>
<td>106</td>
</tr>
<tr>
<td>4</td>
<td>73</td>
</tr>
<tr>
<td>5</td>
<td>30</td>
</tr>
<tr>
<td>6</td>
<td>150</td>
</tr>
</tbody>
</table>

4.2.2 Identification results with limited training data

Next, it is desired to evaluate the performance of both frameworks in the case of limited training data. Both available datasets are segregated into 30% for training and 70% for validation. To tune the SVM parameter pair \((C; \gamma)\), the same cross-validation method is applied. The best cross-validation rates are obtained as 89.735% at \((2^{3.35}; 2^{-2.57})\) and 83.373% at \((2^{5.58}; 2^{-3.64})\) for injection and stamping datasets, respectively. The validation results using the trained SVMs for state classification are shown in Table 5.

<table>
<thead>
<tr>
<th>Table 5</th>
<th>Number of validated segments using our proposed process identification framework with limited training data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Injection dataset cluster</td>
<td>Correct</td>
</tr>
<tr>
<td>1</td>
<td>101</td>
</tr>
<tr>
<td>2</td>
<td>48</td>
</tr>
<tr>
<td>3</td>
<td>144</td>
</tr>
<tr>
<td>4</td>
<td>103</td>
</tr>
<tr>
<td>5</td>
<td>40</td>
</tr>
<tr>
<td>6</td>
<td>208</td>
</tr>
</tbody>
</table>

It can be seen our proposed framework still shows a reliable performance in the case of limited training data. In particular, it classifies 644 out of 667 different segments of injection dataset correctly, thereby yielding an accuracy of 96.55%. For stamping dataset,
An energy data-driven decision support system

482 out of 509 segments are classified correctly yielding an accuracy of 94.69%. Switch off and idle states are still classified very correctly. There is a small classification error arising in warm up state due to misclassification with start up state. It can also be seen that the classification accuracy of moulding, stamping, and abnormal states become worse but still be acceptable, where the corresponding classification errors are 4.80%, 5.47%, and 15.25%, respectively. Most of misclassified segments of abnormal state belong to switch off, idle and warm up states of stamping machine M8, while all segments belonging to stamping state are correctly classified. Since switch off, idle and warm up states are relatively short as compared to stamping state, the abnormal state can be quickly identified. The identification results using the existing framework are of 89.33% and 88.38% accuracies for the injection moulding and stamping datasets, respectively. It can be seen that the performance of the existing framework has dropped significantly in the case of limited training data.

4.3 Comparative discussion

There are several reasons for the advantages of our proposed process identification framework as compared to the existing framework. Instead of preprocessing the raw power data, our proposed framework takes into account the noisy effects using the EBayes threshold method. This completely avoids losing important power features of the data distribution such as relative maxima, minima, and width, etc., which are potentially flattened during noise filtering or signal smoothing.

Another benefit of our proposed framework is the reduction of time delay. As the SG filter is not causal and relies on future data, the existing framework causes extraneous time delay for online applications. The usage of a SG filter with window size $w = w_L + w_R + 1$ in series with a level-$p$ Haar transform delays the wavelet coefficients by $2^p + w_R$ samples from real-time. In the SG filter, the calculated central sample of the fitted polynomial curve is the latest filtered sample. Without loss of generality, let us assume that the real-time sample is currently at index $p_r$, while the SG window still lags behind and only covers up to sample $p_{r-w_R}$. Furthermore, it can be seen from (1) and (2) that the window size of a level-$p$ Haar transform is $2^p$, which means a wavelet coefficient can only be calculated for every $2^p$ smoothed samples. Therefore, the latest wavelet coefficient only represents sample $p_{r-w_R-2^p}$.

In addition, FCM is an unsupervised learning algorithm, where the SVM is of supervised learning type. One uses the FCM to cluster data which their labels are not known a priori, however, the SVM is firstly trained with the labeled data and then is used to classify the unlabeled data. In our industrial applications, the segment labels as well as the number of operational states are all available. This implies that it is more suitable to use the SVM rather than the FCM.

It also can be seen that our proposed framework is effective for imbalanced datasets, as both injection and stamping datasets used in this paper are relatively imbalanced, where classes moulding and stamping dominate the datasets. For the case of highly imbalanced datasets, the classification accuracy of our proposed framework is expected to drop down to 80% at most.
5 Decision-making models

In this section, we discuss useful decision-making models, which use a large-scale data to make energy-efficient, cost-effective, reliable decisions for high-performance manufacturing. Life-cycle analysis is also partially supported herein. The proposed decision-making models are summarised as follows.

- **Energy audit and reporting.** Energy audit and reporting is the inspection, analysis, and documentation of energy consumption in the shop floors. This is often carried out on weekly, monthly, and yearly basis. Over the past decade, industrial energy audit and reporting have exploded as the demand to lower increasingly expensive energy costs and move towards sustainable manufacturing. A knowledge-based approach such as expert systems and case-based reasoning systems are most suitable for this model.

- **Energy-based diagnosis and prognosis.** Energy-based diagnosis and prognosis aims at investigating the relationship between energy consumption and machine faults, and hence using energy consumption as an indirect condition monitoring for industrial machines. This model effectively prevents not only production costs but also excessive energy consumption due to machinery faults, which are common in today’s dynamic manufacturing environment. In current literature, diagnosis and prognosis have been developed using knowledge-based, data-driven, and model-based systems. However, data-driven system is a growing research trend, especially in prognosis and remaining useful life estimation.

- **Energy-based remanufacturing.** Energy-based remanufacturing is the next logical step of energy-based diagnosis and prognosis, which decides to reuse, repair, refurbishing, or recycle faulty machines in an energy-optimal and cost-effective way. Remanufacturing is a relatively new research area. Most existing works often considered only cost effectiveness and customer satisfaction, while energy consumption was hardly studied. As a new research area, all data-driven, model-based, and knowledge-based systems are applicable for remanufacturing.

- **Energy-efficient process planning and scheduling.** Energy-efficient process planning and scheduling can be defined as the arrangements and operations of machines, tools, materials, people, and information to produce energy-efficient workflows and resource assignments. This model may also include cost effectiveness as an optimisation objective and find a Pareto optimal solution. Model-based systems are often applied the process planning and scheduling.

- **FTC.** FTC system ensures the manufacturing system to continue operating properly in the event of the failure of (or one or more faults within) some machines. This model prevents production and energy costs due to unexpected downtime due to machinery failures. Data-driven and model-based systems are often considered in this model.

- **Life-cycle analysis.** Our proposed DSS can contribute as a part of whole life-cycle analysis of the manufactured products, where energy consumption during production cycles are logged and documented. This model supports the environmental sustainability in manufacturing.
The decision-making models described herein provide useful suggestions towards high-performance manufacturing. Although the proposed decision-making models are fully computerised and autonomous, they can also be combined with human decisions.

6 Conclusions

In this paper, we provided a unified DSS architecture. Using real-time energy measurements and process operational states, our proposed DSS made energy-efficient, cost-effective, and reliable decisions for the next generation of high-performance manufacturing. In addition, life-cycle analysis can be partially supported, as energy consumption during the production stage of a product’s life-cycle is accurately logged and documented. To reduce the number of required sensors and amount of logged data, our proposed DSS architecture included an intelligent framework which identifies the process operational states based on energy measurements. To justify our proposed framework, comparative experiments with an existing framework in current literature were evaluated on two industrial applications, an injection moulding system and a stamping system. The experimental results showed that our proposed framework achieved the accuracies of 98.52% and 98.32% in the case of sufficient training data, and 96.55% and 94.69% in the case of limited training data, respectively, which outperformed an existing framework in current literature. Our future work includes developing and implementing the decision-making models on realistic manufacturing systems.

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References


