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# Sensor-Based Recurrence Analysis of Energy Efficiency in Machining Processes

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**ABSTRACT** Manufacturing industry incurs a large portion of energy consumption and carbon emission in the economy. Traditionally, smart energy management depends on aggregated measures from billing information, as well as physics-based models, empirical results derived from extensive experiments, which tend to be limited in the ability for real-time monitoring of energy efficiency. There is an urgent need to develop energy monitoring solutions for more transparency about energy use. This paper presents a new sensor-based approach for recurrence analysis of continuous power signals and multi-state modeling of energy efficiency in the machining process. First, we leverage the recurrence plot to characterize the nonlinear variations in power signals and further help delineate different states in the machining process, thereby providing statistics of energy consumption in each state. Second, we compute the composite index of energy efficiency for each workpiece and then develop multivariate statistical control charts for process monitoring of continuous production of workpieces. Third, after an anomaly is detected, we propose the orthogonal decomposition approach to diagnose the root cause of abnormal states in the energy use. The proposed methodology is evaluated and validated on real-world manufacturing of shaft-like parts in a machine shop. Experimental results show that the prediction error of energy efficiency from sensor-based models is within 5% from the ground truth, which show great potentials to implement sensor-based monitoring and analysis of real-time energy efficiency in the manufacturing process.

**INDEX TERMS** Energy efficiency, process monitoring, recurrence analysis, root cause diagnosis, manufacturing process, sustainable manufacturing.

## I. INTRODUCTION

Manufacturing is a wealth-generating sector in the global economy and provides critical equipment and products for national infrastructure and defense. However, manufacturing industry often incurs big social and environmental costs, e.g., energy consumption and carbon emission. In the U.S., the fuel intensity of manufacturing is about 2.882 thousand British thermal units (Btu) per dollar of output in 2014, and the total manufacturing energy consumption is increased by approximately 3.7% from 2010 to 2014 [1]. The optimization of energy consumption practices and the improvement of energy efficiency are urgently needed for the manufacturing industry. In recent years, several legislative and standardization efforts have been made in order to reduce energy consumption in the industry. For instance, ISO 50001 provides a framework of requirements for organizations to continuously improve energy performance and specify requirements for process and equipment design, measurement and documentation [2]. In addition, EN 16231 suggests an energy-benchmarking methodology to collect and analyze energy data of organizations for the comparison of energy efficiency between or within entities [3]. Also, machine tools are the substantial energy consumer in manufacturing industry. Energy saving depends to a great extent on the energy performance of machine tools. As such, international standards for the environmentally-benign machine tool are introduced. For example, ISO 14955 prescribes the environmental evaluation methods of machine tools, including the design methodology for energy-efficient machine tools and measurement methods for energy consumptions of specific components of machine tools [4], [5].

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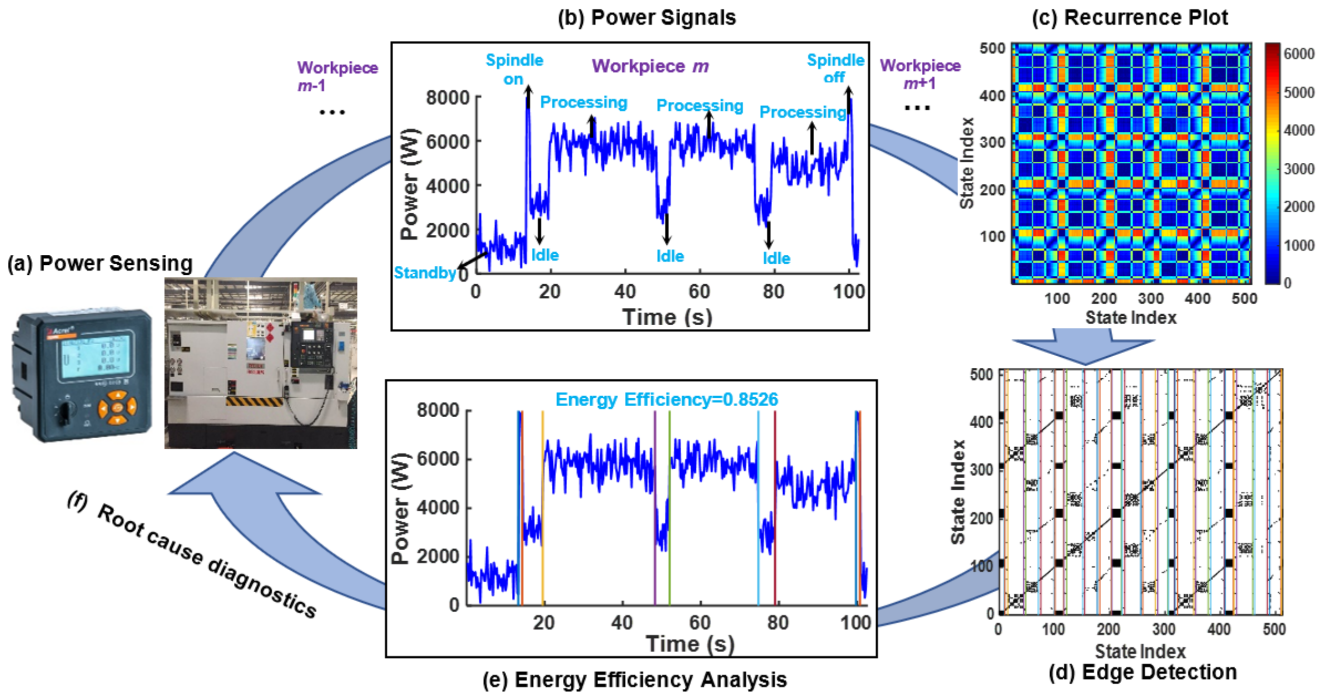


**FIGURE 1.** **The flowchart of proposed research methodology.**

Machining is a key manufacturing process for metal parts, and is widely used due to the high-level geometric accuracy, process reliability, and the ability to perform mass manufacturing of large quantities of parts. However, machining involves the materials-removal process and can be wasteful in terms of both materials and energy consumption [6]. Energy efficiency is the percentage of processing energy consumption in the entire machining process. Note that the machining process is composed of several machine states such as standby, spindle on, idle, processing, spindle off. Prior work showed that the energy consumed for non-processing (or non-cutting) operations is much higher than processing (or cutting) operations [7], [8]. As a result, there are increasing interests on energy monitoring, energy modeling of machining processes, energy efficiency analysis of machine tools, and energy variations due to process parameters or scheduling. In specific, there are urgent needs towards the development of energy monitoring solutions for more transparency about energy use and real-time analysis of energy efficiency [9].

However, little has been done to develop sensor-based models for energy efficiency analysis in the machine shop, which may characterize different machining states, compute real-time energy efficiency of each workpiece, and further detect the anomaly in the manufacturing process without extensive experiments, prior knowledge, as well as big investment on software and machine renovation. The objective of this paper is to develop sensor-based recurrence models for energy efficiency monitoring and root cause diagnosis to analyze the critical factors of energy consumption in the machine shop. As shown in Fig.1, we used the energy meter to collect power signals when each workpiece is cut by the lathe machine. Next, we developed sensor-based recurrence methods for energy efficiency analysis of each workpiece, and the variations of energy consumption from one workpiece to another, thereby performing the root cause diagnostics once an anomaly is detected. Specifically, our contributions in the present investigation are highlighted as follows:

1) This study develops a local recurrence approach for sensor-based analysis of energy efficiency in the machining process, which computes the real-time energy efficiency and detects the anomaly in the manufacturing process of each workpiece.

2) This study has also proposed to use an orthogonal decomposition method to diagnose the root cause of a detected anomaly that delineates the variations of energy use at each state of the machining process.

The remainder of this paper is organized as follows: Section II presents the research background of energy monitoring in a machine workshop. Section III describes the proposed recurrence methodology for energy efficiency analysis of real-time power signals. Sections IV and V show experimental design and results on real-world manufacturing systems. Section VI concludes the present paper.

## II. RESEARCH BACKGROUND

Energy efficiency analysis of machining processes depends to a great extent on the ability to acquire the energy use data with timestamps and detect the machine states (e.g., standby, spindle on, idle, processing, spindle off) [10]. Traditionally, machine shops monitor the variations of energy consumption through aggregated measures in the bills provided by energy suppliers every day or every month [11]. However, this aggregated information tends to be limited to help analyze energy consumption on each machine and the energy efficiency in the machining process. Therefore, small and medium-size machine shops often take an alternative approach to multiply the average value of energy consumption (i.e., in unit time) by the operational time to estimate energy consumption of a machine [12]. This approach is often used when advanced sensing of energy consumption is unavailable, because average ratings of machine energy consumption can often be found in the technical documentation and/or on the specification plate of the machine. However, this method relies on the average statistics and is limited in the ability to capture real-time energy consumption, as well as different machine states. Recently, smart manufacturing calls upon the implementation of advanced sensing of machines and workshops, and then leverages the generated big data to enable the green and sustainable manufacturing [13]. As such, more and more pertinent data about energy use are collected in fine-grained details at machine shops. Realizing full potentials of energy data for sustainable manufacturing depends on the design and development of analytical methods for energy efficiency analysis. In the literature, there are a variety of traditional models and methods for energy efficiency analysis that are discussed as follows.

First, there are early works focusing on the relationship between process parameters and energy consumption. In other words, if machine settings are varied, then how the energy consumption is changed accordingly? However, physics-based models are primarily used in these studies, which have encountered the following gaps: (1) ***Offline experiments***: A large number of experiments are needed to collect data under controlled conditions for statistical modeling and estimation. For example, Diaz *et al*. designed experiments to measure the power demand by a milling machine tool with different material removal rates for energy modeling in the machining process [14]; Balogun *et al*. conducted experiments on a milling machine to investigate the ploughing energy on several types of materials [15]; Hu *et al*. optimized the cutting parameters for improving energy efficiency in machining process based on the experiment data of machine tool's power consumptions on a CNC lathe [16]. (2) ***Engineering knowledge***: Empirical models also demand prior knowledge or expert domain knowledge about the processing plan or machine parameters, which are difficult to be widely implemented in the industry due to high-level variations in processing plans and machine settings. For instance, Abele *et al*. leveraged the process plans from Programmable Logic Controllers (PLCs) to collect energy-relevant data of production machines [17]; Shang *et al*. modeled the variable power flows of the heavy-duty machine tool and use the data of machine parameters such as spindle speed, feed speed, axes position from the NC system for power consumption analysis [18]. (3) ***Online monitoring***: Physics-based experiments and empirical models are often offline and tend to be limited in the ability for real-time analysis of energy efficiency [19].

Second, there are increasing interests to use the power sensor for online monitoring of stochastic variations of energy efficiency in the machining processes. Cyber-physical systems are emerging to leverage the availability of sensor data to construct virtual machine models [20], [21]. Such cyber-physical manufacturing systems focus more on production planning and operations management, and little has been done to monitor stochastic variations of energy consumption in real time. In modern machine shop, advanced power meters are increasingly available to increase information visibility about the machining process and provide rich information pertinent to real-time variations of energy efficiency in the manufacturing process. As the machine will undergo different states in the manufacturing process (e.g., standby, spindle on, idle, processing, spindle off), sensor-based approaches show a higher level of flexibility for energy efficiency analysis. However, it is challenging to investigate the energy consumption in each machine state. In the literature, this is often done through the linkage with control information from the machine. For example, computer numerical control (CNC) codes and PLCs are often used to derive the control information and then help delineate the states of a machine. Shin *et al*. leveraged the processing plan from CNC codes to develop a predictive model of power consumption in manufacturing [22]. Abele *et al*. used the PLC information to analyze the machine states and the energy consumption in each state [17]. Schlechtendahl *et al*. developed an XML-based Energy Information Description Language (EIDL) to store and manage the data of energy consumption in the machines [23]. Chen *et al*. acquired the real-time spindle speed and feed rate through communication with the CNC system to monitor the energy efficiency during the machining processes [24]. In spite of these efforts, it is difficult to retrieve the information about energy consumption at each state during the machining processes because not all machines have PLCs, or other digital control systems, readily available to provide such control information, especially the legacy machines.

There is an urgent need to implement the energy-sensing systems and develop sensor-based models for real-time monitoring and analysis of energy efficiency in the machine shop, which will not only provide the real-time energy efficiency of each workpiece but also detect the anomaly in the manufacturing process without demanding extensive experiments and empirical knowledge.

## III. RESEARCH METHODOLOGY

This research focuses on the real-time monitoring of stochastic variations of energy efficiency in the machining processes. Energy efficiency is an important index about the energy use in the processing state. However, real-time analysis of energy efficiency depends to a great extent on the detection and segmentation of different states (e.g., standby, spindle on, idle, processing, spindle off). As shown in Fig. 1, the first step is to collect real-time power signals in the machining process of each workpiece with energy instrumentations. Second, we represent the nonlinear waveform of power signals in the phase space, and then use the recurrence plot to characterize nonlinear recurrence patterns. Local singularity and nonlinear patterns are delineated by the edge detection algorithms to segment each state of the machining process. Third, we compute the energy consumption in each state and energy efficiency of each workpiece and then develop multivariate statistical control charts to monitor the variations of energy consumption in the production of each workpiece. Finally, after an anomaly is detected, we proposed the orthogonal decomposition approach to diagnose the root cause of the anomaly.

### A. RECURRENCE ANALYSIS OF POWER SIGNALS

As described in Section II, it is difficult to get the information about energy consumption at each state in the machining processes. Therefore, there is an urgent need to fully utilize the available power signals to segment machine states and compute the energy efficiency. Recurrence analysis is widely used for the analysis of nonlinear dynamics in the sensor signals [25]. As the power signals are highly nonlinear and nonstationary, we represent the time series in the phase space so as to study recurrence behaviors within the production of a workpiece, as well as from one workpiece to another. As shown in Fig.1 (c), the phase space representation enables us to characterize nonlinear patterns of power signals in a two-dimensional recurrence plot that provide salient features on the variations of energy consumption.

If the phase space trajectory returns to a neighborhood visited before, this is referred to be a recurrence [26]. The recurrence plot depicts the collection of pairs of time locations at which the trajectory revisits a neighborhood in the phase space, i.e., $\|\vec{x}(i) - \vec{x}(j)\| < \varepsilon$. Fig.1 (c) shows that the unthresholded recurrence plot (UTRP) provides the distances between two states $UR(i,j) = \vartheta(\|\vec{x}(i) - \vec{x}(j)\|)$, where $\|\cdot\|$ is a distance measurement (e.g., the Euclidean norm) and $\vartheta(\cdot)$ is the color code that maps the distance to a color scale. While the thresholded recurrence plot (TRP) only plots the state pairs when the distance $\|\vec{x}(i) - \vec{x}(j)\|$ is below a threshold $\varepsilon$, $R(i,j) = \Theta(\varepsilon - \|\vec{x}(i) - \vec{x}(j)\|)$, where $\Theta$ is the Heaviside function. As shown in Fig.1 (d)), whenever there is a recurrence between $\vec{x}(i)$ and $\vec{x}(j)$, the $(i, j)$ location will be marked as a black dot. Otherwise, there will be a white dot in TRP.

### B. PHASE SPACE SEGMENTATION

Because the ridges in the TRP denote the dynamic transitions of power signals, we further propose to segment machine states by edge detection of the recurrence plot as shown in Fig. 1(d). The dynamic transitions between various local homogeneous sets, resulting from the underlying chaotic dynamics and/or non-stationarities, are detected with the use of image edge detection filters. In this paper, we utilize the Sobel operators to detect the ridges and nonstationary transitions in the recurrence plot. The Sobel operators $I_a$ and $I_b$ consists of a pair of $3 \times 3$ convolution kernels as follows:

$$I_a = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix}, \quad I_b = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{1}$$

These kernels are designed to identify nonlinear and nonstationary edges along the vertical and horizontal directions in a recurrence plot, one kernel for each orientation. The local gradient magnitude gives the information of edge strength as $G_{a,b} = \sqrt{G_a^2 + G_b^2}$, where $G_a$ and $G_b$ are horizontal and vertical gradient estimations, respectively, defined as follows:

$$G_a = I_a * R \quad \text{and } G_b = I_b * R \tag{2}$$

where $*$ is the convolution sign and $R$ is the TRP.

As such, nonhomogeneous structural patterns in the recurrence plot are delineated and estimated to provide the transition dynamics among machine states in the power signals. Although the Sobel operators are utilized in this paper, the selection of filters could be optimized for different case studies. It does not preclude others to choose a better filter for a different case study. Most importantly, the edge detection methods should characterize the nonlinear transitions in the system dynamics. In this investigation, we characterized and delineated five states for each workpiece in the machining process, including standby, spindle on, idle, processing, and spindle off, see Fig.1 (e).

### C. ENERGY EFFICIENCY ANALYSIS AND PROCESS MONITORING

Energy efficiency is an important index to help identify the issues in technical and managerial operations of a machine shop. The energy efficiency index of each workpiece is defined as the percentage of energy consumption of processing states in the whole machining process. In the theory, energy is the integral of power signals over time, and the energy efficiency index is calculated as the sum of energy consumption in processing states divided by the total energy in the whole machining process. As we described above, traditional methods often employ offline experiments and engineering knowledge for energy modeling, but tend to be limited in the ability for real-time energy efficiency analysis. Based on the phase-space segmentation results of recurrence plots in Section III. B, real-time estimation of machine states and energy efficiency analysis can be achieved without physics-based experiments and empirical models, where the energy efficiency index for each workpiece is calculated as follows:

$$E = \frac{\sum_{c=1}^{C} E_c}{E_T} \tag{3}$$

where $C$ is the number of processing states, $E_c$ is the energy of processing state $c$, $c = 1, \cdots, C$, and $E_T$ is the total energy consumption of the workpiece.

Further, we develop the multivariate control chart, i.e., Hotelling's $T^2$, to monitor the energy consumption at different states in the machining process of each workpiece.

Because there are a number of machine states, energy measures in each state generate a multi-dimensional energy vector $\mathbf{x}_m = [x_{m1}, \cdots, x_{mP}]^T$ for a workpiece $m$, where $P$ is the total number of machine states (e.g., standby, spindle on, idle, processing, spindle off). The $T^2$ statistic is defined as the generalized distance from the energy vector $\mathbf{x}_m$ of the workpiece $m$ to the sample mean of energy matrix from $M$ workpieces $\mathbf{X}_{M\times P} = [\mathbf{x}_1, \cdots, \mathbf{x}_M]^T$.

$$T_m^2 = (\mathbf{x}_m - \bar{\mathbf{x}})^T \mathbf{S}^{-1} (\mathbf{x}_m - \bar{\mathbf{x}}) \quad (4)$$

where, $\bar{\mathbf{x}}$ and $\mathbf{S}$ are the mean vector and covariance matrix obtained from $M$ workpieces. The upper control limit of Hotelling's $T^2$ statistic is UCL $= \frac{P(M+1)(M-1)}{M^2-MP} F_{\alpha,P,M-P}$, where $F_{\alpha,P,M-P}$ is the upper $100\alpha\%$ of $F$ distribution with degrees-of-freedom of $P$ and ($M$-$P$), see more details of $T^2$ control limits in [26].

However, the inversion of covariance matrix $\mathbf{S}$ is often difficult because the dimensionality of energy vectors is large and thereby potentially leads to the issue of "curse of dimensionality" [27]. In order to tackle this challenge, the energy matrix $\mathbf{X}_{M\times P}$ is transformed into a set of principal components that are linearly uncorrelated. In details, the first step is to center $\mathbf{X}_{M\times P} = [\mathbf{x}_1, \cdots, \mathbf{x}_M]^T$ by subtracting the sample mean, i.e., $\mathbf{X}_C = [\mathbf{x}_1 - \bar{\mathbf{x}}, \cdots, \mathbf{x}_M - \bar{\mathbf{x}}]^T$, then $\mathbf{X}_C$ is decomposed by the singular value decomposition (SVD) as

$$\mathbf{X}_C = \mathbf{U}\psi\mathbf{V}^T \quad (5)$$

where $\mathbf{U}$ and $\mathbf{V}$ are $M \times M$ and $P \times P$ orthonormal matrices respectively, and $\boldsymbol{\psi}$ is a $M \times P$ diagonal matrix with diagonal entries $\psi_{11} \geq \psi_{22} \geq \cdots \geq \psi_{PP} \geq 0$ that are the eigenvalues of $\mathbf{X}_C$. The corresponding principal components are defined as $\mathbf{Z} = \mathbf{X}_C * \mathbf{V} = \mathbf{U}\psi\mathbf{V}^T\mathbf{V} = \mathbf{U}\psi$. Moreover, the original energy matrix can be reconstructed as $\mathbf{X}_C = \mathbf{Z}\mathbf{V}^{-1} = \mathbf{Z}\mathbf{V}^T$. Then the covariance of energy matrix can be reformulated as

$$\mathbf{S} = \frac{\mathbf{X}_\mathbf{c}^T\mathbf{X}_C}{M-1} = \frac{\mathbf{V}\mathbf{Z}^T\mathbf{Z}\mathbf{V}^T}{M-1} = \mathbf{V}\mathbf{S}_z\mathbf{V}^T \quad (6)$$

where $\mathbf{S}_z$ is the covariance matrix of principal components, and $\mathbf{S}_z$ is a diagonal matrix whose elements are $\psi_{pp}, p = 1, 2, \cdots, P$. The $T^2$ statistic of the $P$-dimensional energy vector of workpiece $m$ will be calculated as

$$\begin{aligned} T_m^2 &= (\mathbf{x}_m - \bar{\mathbf{x}})^T \mathbf{S}^{-1} (\mathbf{x}_m - \bar{\mathbf{x}}) \\ &= \mathbf{Z}_m\mathbf{V}^T\mathbf{S}^{-1}\mathbf{V}\mathbf{Z}_m^T = \mathbf{Z}_m\mathbf{V}^T(\mathbf{V}\mathbf{S}_z\mathbf{V}^T)^{-1}\mathbf{V}\mathbf{Z}_m^T \\ &= \mathbf{Z}_m\mathbf{S}_z^{-1}\mathbf{Z}_m^T = \sum_{\mathbf{p}=\mathbf{1}}^{\mathbf{P}} \frac{Z_{mp}^2}{\psi_{pp}^2} \end{aligned} \quad (7)$$

### D. ROOT CAUSE DIAGNOSIS

In the machining process, there are a number of factors that may lead to the variations of energy consumption at each state. For example, tool wear will cause an elevation of energy consumptions in the processing state. The chatter often leads to a larger variation in the energy consumption. Also, the quality of raw materials will result in the changes in energy usage. Bustillo *et al.* revealed that the feed power consumption rises slowly due to tool wear until insert breakage occurs [28]. There are progressive dissimilarities found between two energy profiles. The quantification of such pattern differences will be conducive to condition monitoring of machines and tools. As such, we propose the use of orthogonal decomposition method [29] to interpret multivariate control signals and analyze the root cause of the anomaly in energy usage. In other words, if the $T^2$ statistic from the workpiece $m$ goes out-of-control, root cause analysis focuses on the questions "which machine state is the cause of anormaly in the multi-dimensional energy vector $\mathbf{x}_m$?"

Here, the Hotelling's $T^2$ statistic of a workpiece $m$ in (7) can be decomposed into $P$ orthogonal elements as

$$T_m^2 = t_{m[1]}^2 + t_{m[2\cdot1]}^2 \cdots + t_{m[P\cdot1,2,\cdots,P-1]}^2 \quad (8)$$

where $t_{m[p]}^2$ is the unconditional term for a specific state $p$ in the $P$-dimensional energy vector $\mathbf{x}_m$, defined as follows:

$$t_{m[p]}^2 = (x_{mp} - \bar{\mathbf{x}}_p)^2 / s_p^2, \quad p = 1, 2, \cdots, P \quad (9)$$

where $\bar{\mathbf{x}}_p$ and $s_p^2$ are the mean and variance estimates of energy vector for the state $p$. The critical value for the unconditional terms is UCL$_1 = \frac{(m-1)^2}{m}\beta(\frac{1}{2}, \frac{m-2}{2})$, where $\beta(\frac{1}{2}, \frac{m-2}{2})$ is the Beta distribution with parameters $\frac{1}{2}$ and $\frac{m-2}{2}$. On the other hand, $t_{m[p\cdot1,2,\cdots,p-1]}^2$ is a conditional term which is given as

$$t_{m[p\cdot1,2,\cdots,p-1]}^2 = \frac{(x_{mp} - \bar{\mathbf{x}}_{p\cdot1,2,\cdots,p-1})^2}{s_{p\cdot1,2,\cdots,p-1}^2}, \quad p = 1, 2, \cdots, P \quad (10)$$

The conditional term is adjusted by the estimates of the mean and standard deviation of the conditional distribution of $x_{mp}$ given $x_{m1}, x_{m2}, \cdots, x_{mp-1}$. The critical value for the conditional terms is UCL$_2 = \frac{(m-1)^2}{m}\beta(\frac{1}{2}, \frac{m-g-2}{2})$, where $g = p - 1$ is the number of variables being conditioned.

The orthogonal decomposition method provides a greater level of flexibility to identify the root cause when an out-of-control is signaled, given the existence of correlations among machine states in the multi-dimensional energy vector. However, if the dimensionality $P$ is high, then the number of decompositions that need be conducted in (8) will reach $P \times 2^{(P-1)}$. This incurs a higher level of computational complexity [30]. Hence, we propose a sequential computational scheme to efficiently compute the orthogonal decomposition of $T^2$ statistic as shown in Fig.2.

First, the unconditional decomposition term $t_{m[p]}^2$ for a state $p$ is computed.If $t_{m[p]}^2$ is significant, the $p$th state variable is one of the root causes. Then, we remove the state $p$ from the energy vector to re-compute the $T_m^2$ for the remaining state variables. If the $T_m^2$ statistic is not significant, there is no other root cause for the out-of-control. In other words, the anomaly of workpiece $m$ is due to the state $p$ in the machining process. If the $T_m^2$ statistic is still significant after the removal of state $p$, then there exist other root causes and we go to the next step.

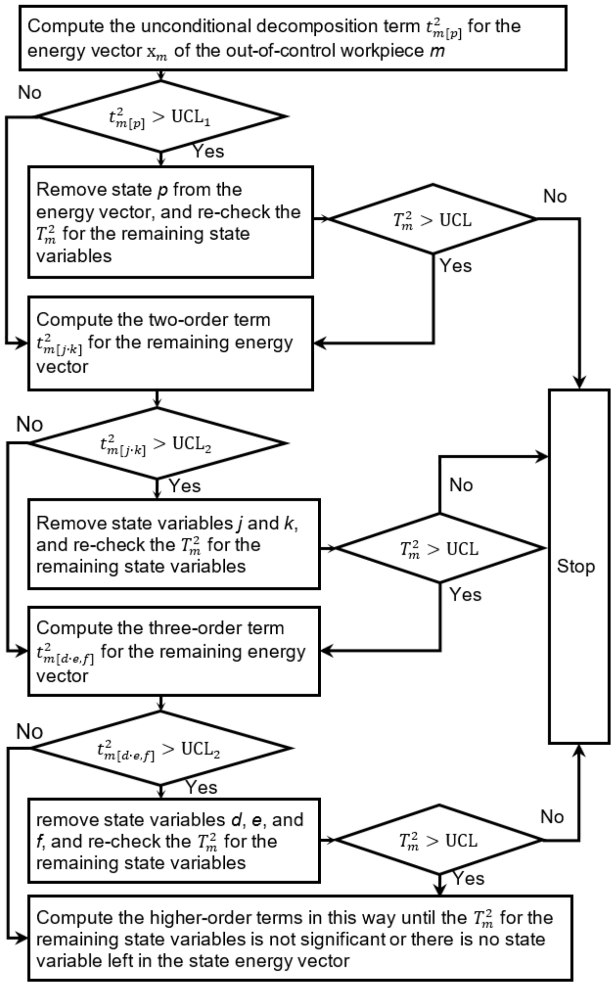


**FIGURE 2. The flowchart of sequential orthogonal $T^2$ decomposition.**

Second, the two-order conditional term $t^2_{m[j\cdot k]}$ is computed, where $j \neq k$, for the energy vector of remaining state variables. If $t^2_{m[j\cdot k]}$ is significant, then the $j$th and $k$th state variables are two root causes. After removing them from the energy vector, we re-check the $T^2_m$ for the remaining state variables. If it is not significant, there is no other root cause for the out-of-control. In other words, the anomaly of workpiece $m$ is related to the bivariate relationship of the state $j$ and $k$. If the $T^2_m$ is still significant, we go to the next step.

Third, the three-order conditional term $t^2_{m[d\cdot e,f]}$ is computed, where $d \neq e \neq f$. If $t^2_{m[d\cdot e,f]}$ is significant, then the $d$th, $e$th, and $f$th states are three root causes. After removing them from the energy vector, we re-check the $T^2_m$ for the remaining state variables. If it is not significant, there is no other root cause for the out-of-control. The anomaly of workpiece $m$ is related to the triple variate relationship of the state $d$, $e$, and $f$. If the $T^2_m$ statistic is still significant, we go to the next step.

Finally, we continue computing the higher-order terms in this way until the $T^2_m$ for the remaining state variables is not significant or there is no state variable left in the state energy vector. It is common that primary variables causing the significant $T^2$ statistic can be found after examining only the two-order and three-order conditional terms. In our case study, we found that the sequential algorithm is efficient in identifying the root cause of an anomaly in energy consumption.

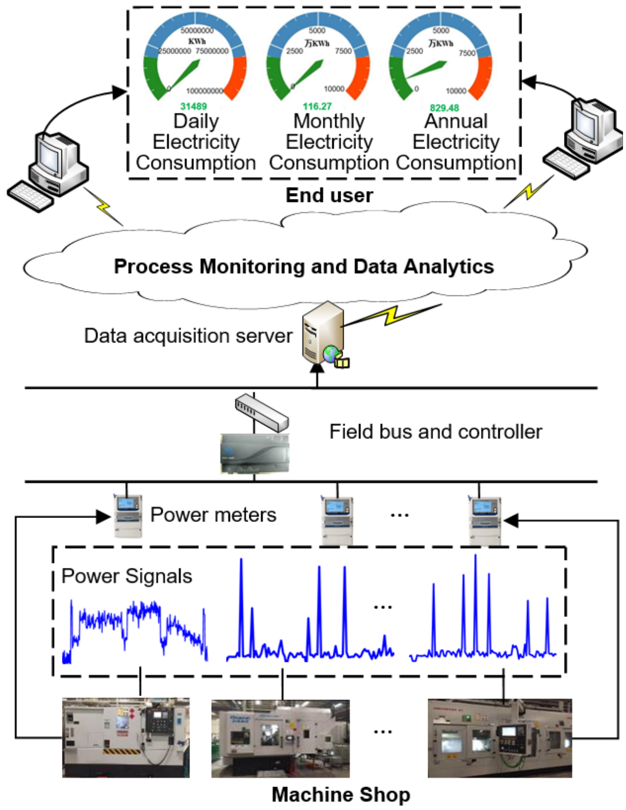


**FIGURE 3. The system diagram of energy-sensing systems implemented in the machine shop.**

## IV. EXPERIMENTAL DESIGN AND MATERIALS

Energy-aware sensing of machining processes is imperative to circumvent extensive experiments for energy modeling and real-time energy efficiency analysis. As shown in Fig.3, we implemented the advanced energy sensing and monitoring system for experimental studies in a machine shop. In this investigation, we installed high-precision power meters (i.e., Acrel AEM96) on the power inlet of each machine to measure electric voltage and current signals. The voltage and current data are then communicated to the data acquisition system, namely DYNC-MiniFC, through the RS485 protocol. Further, large amounts of data from multiple machines are sent through Industrial Ethernet to the data storage server in the factory. End users will be able to read and visualize the data from the server through client computers. As a vertical step, we propose to develop new sensor-based recurrence models for real-time energy efficiency analysis and root cause diagnosis to analyze critical factors of energy consumption in the machine shop.

As shown in Fig. 1(b), there are a number of different states in the machining process, which can happen

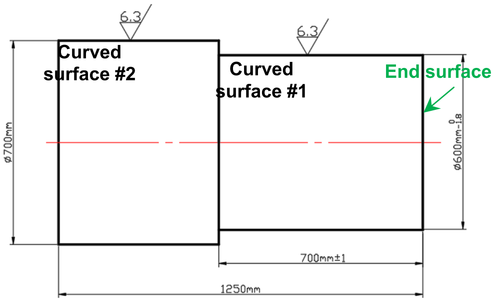


FIGURE 4. The CAD file and process plan for the machining operation.

successively and in periodic cycles when workpieces are near-periodically produced in high volume and low mix. Diaz *et al*. discussed the energy efficiency in discrete-manufacturing systems and showed that operational models should be customized for different types of machine tools [9]. Palasciano *et al*. delineated five operational states for a milling machine, i.e. switch-off (off), stop (stop), pre-processing (Pre-processing), ready (Ready) and executed a CAM Program on a workpiece (Processing) [31]. Chen *et al*. focused on the machining center and used the following states for energy efficiency analysis, including power off state, start-up state, standby state, spindle acceleration/deceleration state, air cutting state and cutting state [24]. In the present study, we focus on the machining process of workpieces and hence are less concerned about switch on and off of the machine tool. Although some papers may name the states in different ways, for example, using "standby" or "ready" to represent the same state, this paper is consistent with the majority of studies in the state of the art. Based on ISO 14955-1:2017 standard and field experiments, we define the states in the machining processes as the following:

- **Standby**: The machine is in the standby state after it is turned on while the drive systems are still off.
- **Ready for processing**: All functions of the machine are running except the cutting. The machine is ready for processing, which is also called "idle" in some studies.
- **Spindle on/off**: There is often a peak in power signals when the spindle is turned on/off.
- **Processing**: The workpiece is in the process of cutting.

It is imperative to characterize and delineate machine states in the power signals so as to compute the energy efficiency index, i.e., the percentage of energy consumption of processing states in the whole machining process. Here, we propose the use of recurrence methods for real-time energy efficiency analysis in the machining process, as shown in the case study below.

## V. EXPERIMENTAL RESULTS

### A. REAL-WORLD CASE STUDY IN THE MACHINING PROCESS

The proposed methodology is evaluated and validated with real-world machining experiments of shaft-like parts in a gear-box factory. As shown in Fig. 4, the same CAD design is used for the cyclic production of 70 workpieces, which consists of three cutting surfaces, i.e., end surface, curved surface #1 and curved surface #2. The diameter of end surface is 60cm, the length of curved surface #1 is 70cm, the length of curved surface #2 is 55cm, the diameter of curved surface #2 is 70cm, and the surface roughness is marked as 6.3 $\mu m$. The present study focuses on energy consumptions in each step of the machining process, as well as the variations of energy efficiency from one workpiece to another one.

TABLE 1. The steps of the process plan.

| Order | Machining Steps | Machining controls | Machining states | Spindle speed |
|---|---|---|---|---|
| 1 | Cut curved surface #1 | Machine on | Startup | 0 |
| | | Tool setting | Standby | 0 |
| | | Turing on spindle | Spindle on | 0 |
| | | Cut-in | Idle | 600 |
| | | Cut surface #1 | Processing | 600 |
| | | Cut-out | Idle | 600 |
| 2 | Cut curved surface #2 | Cut-in | Idle | 1000 |
| | | Cut surface #2 | Processing | 1000 |
| | | Cut-out | Idle | 1000 |
| 3 | Cut end surface | Cut-in | Idle | 1000 |
| | | Cut end surface | Processing | 1000 |
| | | Turn off spindle | Spindle off | 1000 |

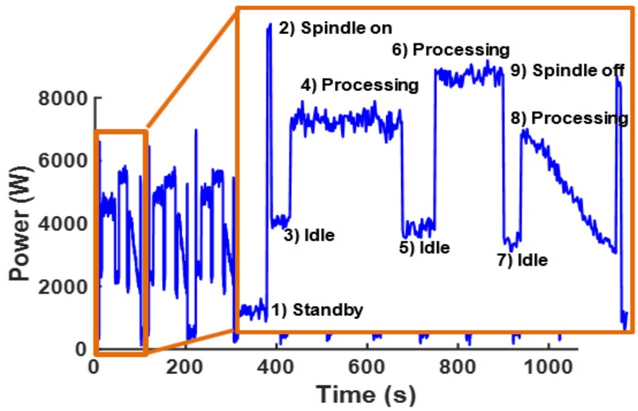


FIGURE 5. The variations of power signals with respect to machining process and control steps.

As shown in Table 1, all the workpieces are produced with the CNC machines in the Batch mode. There are three processing steps - end surface, curved surface #1 and curved surface #2 – for each workpiece. According to the process plan, the CNC codes are designed to implement machine controls to meet with the production requirement in each processing steps of the CAD design. Note that due to different controls in the process plan, the machining process consists of various states such as standby, spindle on/off, idle, processing. In addition, spindle speeds are varied from 0 to 600 and 1000 rpm in the machining processes.

As shown in Fig.5, because of the production requirements in CAD design and process plan, the waveforms of power signals are varying in the machining process. Although workpieces are near-periodically produced according to the

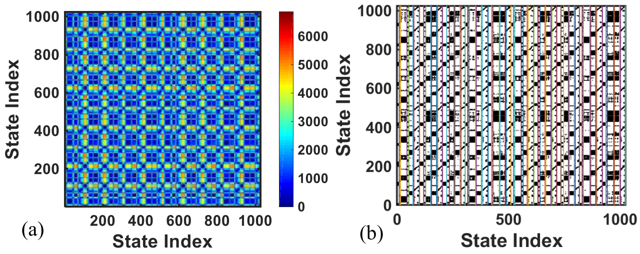


**FIGURE 6.** The recurrence plot (a) and phase segmentation (b) of power signals.

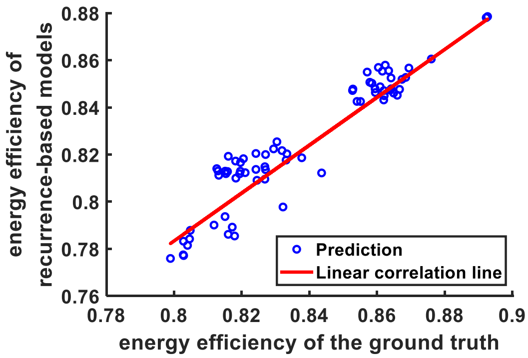


**FIGURE 7.** The comparison of energy efficiency indices between recurrence- based models and the ground truth.

process plan in Table 1, there are also variations in power signals from one workpiece to another. We have also showed a zoom-in subfigure of a workpiece in Fig. 5, which also consists of 9 machining states. Now, the next step is to perform recurrence analysis of power signals and segment the states for energy efficiency analysis, without explicit assumption of full knowledge in each step of machine controls.

As shown in Fig.6, recurrence plots help delineate and characterize the important nonstationary structural patterns in the power signals. Note that nonlinear and nonstationary signals can be piece-wisely decomposed into a number of linear and stationary segments. After applying the Sobel operators, edges provide pertinent information about the boundaries of linear and stationary segments, which are high-frequency abruptions in the recurrence plot. As such, machine states are effectively delineated for the next step of energy efficiency analysis, which can be done within the power signals from a workpiece, or be benchmarked from one workpiece to another one.

As shown in Fig.7, we collected the power signals from 70 workpieces in the experiment, computed the energy efficiency indices with the proposed recurrence-based methods, and then benchmarked computational results with the ground truth. The ground truth is established by manual segmentation of machine states and energy computation with the raw data from the power meter for each machining state, which are labor intensive. The energy consumption in each state is calculated by the following equation:

$$E_{mp} = \sum 0.25 \times \left\| \vec{x}_{mp} \right\| \tag{11}$$

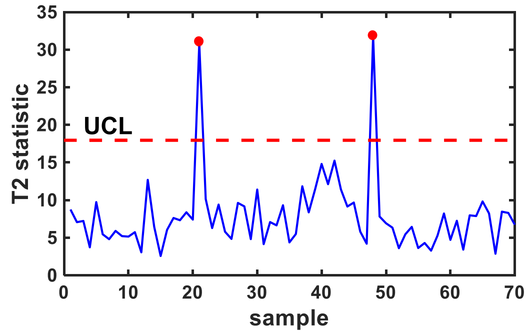


**FIGURE 8.** The $T^2$ control chart of 70 workpieces.

**TABLE 2.** The orthogonal $T^2$ decomposition.

| Variable ($x_{mi}$) | Workpiece 21 $t^2_{m[p]}$ | Workpiece 48 $t^2_{m[p]}$ |
|---|---|---|
| $x_{m1}$ | 0.8627 | 0.6162 |
| $x_{m2}$ | 1.2933 | 0.1706 |
| $x_{m3}$ | 0.8632 | 0.8696 |
| $x_{m4}$ | 23.2007 | 23.2659 |
| $x_{m5}$ | 0.5817 | 0.5936 |
| $x_{m6}$ | 0.1249 | 0.1230 |
| $x_{m7}$ | 0.0703 | 0.0858 |
| $x_{m8}$ | 2.5235 | 2.5132 |
| $x_{m9}$ | 0.2553 | 0.3220 |

where $E_{mp}$ denotes the energy consumption of workpiece $m$ under state $p$, $\vec{x}_{mp}$ is the power vector of workpiece $m$ under state $p$, 0.25 is the time interval of sensing system (i.e., the data acquisition frequency, 4 data points in one second). Fig. 7 shows that energy efficiency results computed from the recurrence method are highly correlated with the ground truth. The $R^2$ value is approximately 94.48% between recurrence predictions and the ground truth. Experimental results show that the prediction error of recurrence method is less than 5% from the ground truth.

Further, we computed the $T^2$ statistic based on the 9-dimensional energy vector obtained from each workpiece. The $T^2$ control chart helps monitor the variations of energy consumptions from one workpiece to another. In total, there are 70 workpieces and each follows the same process plan with 9 machining states. With the significance level of 0.1, the upper control limit (UCL) is computed as 17.95. As shown in Fig.8., two workpieces are out-of-control and yield the $T^2$ statistic larger than the UCL. The $T^2$ statistic for the two out-of-control workpieces are 30.8173 and 31.7695 respectively.

Next, we performed the sequential computation scheme for orthogonal decomposition of $T^2$ statistic to identify the root cause of two anomalies in the energy usage. Table 2 shows the results of the first step in Fig.2 to compute the unconditional decomposition term $t^2_{m[p]}$ for two out-of-control workpieces, i.e., workpieces 21 and 48. It may be noted that $t^2_{m[4]}$ is significant and therefore we removed the state variable $x_{m4}$ from the energy vector. Then we computed the $T^2_m$ of workpieces 21 and 48 for the remaining state variables, which are 7.6166 and 8.5036 respectively. In the second step, the new $T^2$ statistic are no longer significant. The orthogonal $T^2$

**TABLE 3. Performance comparison between shewhart and recurrence $T^2$ charts.**

| Mean Shift | Variation Shift | $ARL_1$ for state 4 | | $ARL_1$ for state 6 | | $ARL_1$ for state 8 | |
|---|---|---|---|---|---|---|---|
| | | Shewhart | Recurrence $T^2$ | Shewhart | Recurrence $T^2$ | Shewhart | Recurrence $T^2$ |
| +0.02 | 0.005 | inf | 29.67 | inf | 49.02 | inf | 84.75 |
| | 0.01 | inf | 19.16 | 2000.00 | 28.17 | inf | 35.21 |
| | 0.015 | inf | 12.06 | 476.19 | 18.18 | inf | 19.27 |
| +0.04 | 0.005 | inf | 3.55 | 416.67 | 5.51 | inf | 4.87 |
| | 0.01 | inf | 3.31 | 60.61 | 5.19 | inf | 4.61 |
| | 0.015 | inf | 3.08 | 33.22 | 4.99 | inf | 4.27 |
| +0.12 | 0.005 | 16.03 | 1.00 | 1.22 | 1.00 | inf | 1.00 |
| | 0.01 | 13.77 | 1.00 | 1.22 | 1.00 | inf | 1.01 |
| | 0.015 | 10.18 | 1.00 | 1.22 | 1.01 | 3333.00 | 1.01 |
| +0.15 | 0.005 | 2.24 | 1.00 | 1.05 | 1.00 | 833.33 | 1.00 |
| | 0.01 | 2.35 | 1.00 | 1.05 | 1.00 | 92.59 | 1.00 |
| | 0.015 | 2.46 | 1.00 | 1.05 | 1.00 | 37.17 | 1.00 |
| -0.02 | 0.005 | inf | 23.53 | 94.34 | 51.28 | inf | 24.39 |
| | 0.01 | inf | 16.53 | 50.25 | 25.51 | inf | 17.45 |
| | 0.015 | inf | 11.81 | 33.00 | 16.23 | inf | 12.35 |
| -0.04 | 0.005 | inf | 4.26 | 10.41 | 5.38 | inf | 4.46 |
| | 0.01 | inf | 3.68 | 10.87 | 5.11 | inf | 4.28 |
| | 0.015 | inf | 3.32 | 10.86 | 4.56 | inf | 3.93 |
| -0.12 | 0.005 | 8.94 | 1.00 | 1.16 | 1.01 | inf | 1.00 |
| | 0.01 | 7.69 | 1.00 | 1.18 | 1.02 | 303.03 | 1.01 |
| | 0.015 | 6.76 | 1.00 | 1.21 | 1.02 | 83.33 | 1.01 |
| -0.15 | 0.005 | 2.51 | 1.00 | 1.00 | 1.00 | 6.87 | 1.00 |
| | 0.01 | 2.58 | 1.00 | 1.00 | 1.00 | 7.74 | 1.00 |
| | 0.015 | 2.72 | 1.00 | 1.01 | 1.00 | 8.10 | 1.00 |

decomposition shows that there is an anomaly in the first processing state (i.e., state $x_{m4}$). After checking the power signals of the workpieces, we found the standardized machining process generates abundant data in the "in-control" state of energy efficiency. This, in turn, provides a great opportunity to establish confidence intervals for energy efficacy monitoring. As a result, hypothesis testing has been formulated in terms of Hotelling T2 control charts for the detection of abnormalities in energy efficiency. Please note that this problem setting is different from classification of highly imbalanced dataset. The mean powers of workpiece 21 and 48 in the first processing state are 11.98% and 11.13% higher than other workpieces, respectively. In addition, the variances of workpiece 21 and 48 are 2.11% and 3.14% bigger than other workpieces. In the future work, we will carry out more experiments to investigate the factors influencing the energy usage in processing states.

### B. SIMULATION EXPERIMENTS FOR PERFORMANCE COMPARISON

Furthermore, we conducted simulation experiments to evaluate and validate the performance of recurrence $T^2$ control chart for the monitoring of energy variations in the machining process. Simulation experiments are designed on the basis of real-world data about energy usage during the machining processes. First, we collect a total of 100 in-control samples of power signals, and then simulate 100 out-of-control samples in three processing states (i.e., States 4, 6, or 8, also see Fig. 5) by adding the mean shifts and variation shifts to evaluate the performance of recurrence $T^2$ charts. In this study, we have generated 8 levels of mean shifts, including ±0.02, ±0.04, ±0.12, ±0.15, and 3 levels of variation shifts (i.e., 0.005, 0.01, 0.015 in terms of standard deviation). In total, there are 24 experimental scenarios for each processing state to evaluate the performance of recurrence $T^2$ charts and then make comparisons with traditional Shewhart charts.

The Shewhart control charts for three processing states are calculated as

$$UCL = \bar{\bar{x}}_p + 3\frac{\bar{R}_p}{d_2} \tag{12}$$

$$CL = \bar{\bar{x}}_p \tag{13}$$

$$LCL = \bar{\bar{x}}_p - 3\frac{\bar{R}_p}{d_2} \tag{14}$$

where $UCL$ and $LCL$ are the upper control limit and lower control limit, $CL$ denotes the center line, $\bar{\bar{x}}_p$ is the average of the energy vector $\boldsymbol{x}_p$ for state $p$ ($p = 4$, 6 and 8 respectively), $\bar{R}_p$ is the average of moving ranges of two successive samples,

$R_{np}$, $R_{np} = \left|x_{np} - x_{(n-1)p}\right|$, $n = 2, \cdots, N$, $d_2$ is a tabulated constant for various sample sizes. Here, the sample size of moving range is 2, hence $d_2 = 1.128$.

Average run length (ARL) is used as the performance metric to benchmark different monitoring schemes. Average run length is the average interval between the start of the monitoring and the signaling of the first out-of-control sample. ARL is often computed by the inversion of average alarm rate in practice. In this study, we used the out-of-control ARLs (i.e. $\text{ARL}_1$). It is worth mentioning that the smaller the $\text{ARL}_1$ is, the better the monitoring scheme. In each experimental scenario, we simulate 100 out-of-control samples with mean and variation shifts, and then compute $\text{ARL}_1$s by randomly replicating the experimental scenario for 100 times.

Table 3 shows the experimental results of performance comparison between Shewhart and recurrence $T^2$ control charts for 24 scenarios of varying levels of mean and variation shifts in the processing states of power signals. We replicated the experiments 100 times for each scenario. As shown in Table 3, it is evident that recurrence $T^2$ charts are more agile than Shewhart chart. When the mean shift increases to $|\pm 0.15|$, all $\text{ARL}_1$s of recurrence $T^2$ charts reach 1.00, which means the anomaly in energy usage is immediately signaled when it emerges. However, $\text{ARL}_1$s of Shewhart charts are close to 1.00 for the processing state 6. For instance, Shewhart control chart has $\text{ARL}_1$ value of 1.05 when mean shift $= 0.15$ and standard deviation shift $= 0.015$ for the processing state 6. Generally, the $\text{ARL}_1$s of either Shewhart or recurrence $T^2$ charts decrease when the mean shifts and standard deviation shifts are getting bigger. In other words, it is much easier to signal the alarm when the shift magnitudes are bigger. However, recurrence $T^2$ charts detect the out-of-control much faster than Shewhart chart. When the standard deviation shifts are decreased, most of the $\text{ARL}_1$s for Shewhart charts increase in a much higher pace than recurrence $T^2$ charts.

## VI. CONCLUSION

In this paper, we propose new recurrence-based models for real-time energy efficiency analysis and anomaly detection in the machining process. Recurrence analysis is shown to effectively characterize the nonlinear variations in the power signals and further help delineate different states in the machining process. Further, we develop the Hotelling's $T^2$ chart for the anomaly detection and then perform the orthogonal decomposition to pinpoint the root causes in the machining process. The proposed recurrence methods are low cost and data-driven without the stringent requirements of extensive experiments and equipment upgrade. Experimental results show the proposed approach has great potential to enable the implementation of sensor-based models for real-time energy efficiency analysis in the manufacturing process.

Our future research will focus on a new network monitoring approach of energy efficiency for a large number of machines with the use of energy sensing systems and cross-recurrence approaches. The power signals from different machines will be analyzed by the cross-recurrence method so that the anomaly of energy efficiency in the machine shop can be detected. In addition, after the root cause is identified, we will investigate the optimal control policies of machine tools through communication with PLCs and NC systems, thereby improving the production quality and energy efficiency.

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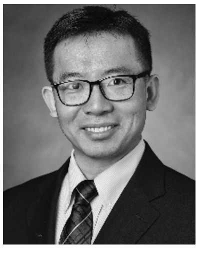

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