Exploring Equipment Electrocardiogram Mechanism for Performance Degradation Monitoring in Smart Manufacturing

Baotong Chen, Jiafu Wan, *Member, IEEE*, Min Xia, and Yu Zhang

***Abstract*—Similar to the use of electrocardiogram (ECG) for monitoring heartbeat, this article proposes an equipment electrocardiogram (EECG) mechanism based on fine-grained collection of data during the entire operating duration of the manufacturing equipment, with the purpose of the EECG to reveal the equipment performance degradation in smart manufacturing. First, the system architecture of EECG in smart manufacturing is constructed, and the EECG mechanism is explored, including the granular division of the duration of the production process, the matching strategy for process sequences, and several important working characteristics (e.g., baseline, tolerance, and hotspot). Next, the automatic production line EECG (APL-EECG) is deployed, to optimize the cycle time of the production process and to monitor the performance decay of the equipment online. Finally, the performance of the APL-EECG was validated using a laboratory production line. The experimental results have shown that the APL-EECG can monitor the performance degradation of the equipment in real-time and can improve the production efficiency of the production line. Compared with a previous factory information system, the APL-EECG has shown more accurate and more comprehensive understanding in terms of data for the production process. The EECG mechanism contributes to both equipment fault tracking and optimization of production process. In the long run, APL-EECG can identify potential failures and provide assistance in for preventive maintenance of the equipment.**

***Index Terms*—Equipment electrocardiogram (EECG), performance degradation monitoring, production optimization, smart manufacturing.**

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I. Introduction

ARITIFICIAL intelligence (AI) is the core driver behind high-grade transformation of manufacturing. With the rapid integration of manufacturing and information technologies, such as computing, communication, and control, AI can facilitate the smart manufacturing system in obtaining the abilities of autonomous perception, abnormality detection, health management, and preventive maintenance. An intelligent production line of industry 4.0 needs to meet the requirements of multivariety, small batch, and personalized customization production modes [1], [2]. Meanwhile, it puts forward stringent requirements for the safety, reliability, and maintainability of the manufacturing equipment. However, the use of intelligent equipment will inevitably lead to its performance degradation. Inspired by the human electrocardiogram (ECG), we propose using an equipment ECG, called EECG, to determine performance degradation rules for manufacturing equipment. As the equipment operates over fine-grained time slots, the goal of using the EECG is to monitor the performance degradation and optimize the cycle time of the production line. The EECG can identify potential issues, assist the intelligent production line in achieving preventive maintenance before an equipment fault actually occurs, and eventually form a closed loop of "monitoring–diagnosis–maintenance" strategy.

With the help of a mature data acquisition system, as shown in Fig. 1, the visualization of the production process contributes to making the production process more transparent. Archer *et al.* [3] proposed a task-oriented framework in data space for fine-grained data integration and data management, which is useful for storing fine-grained data and querying current states of the smart device. The ubiquitous industrial Internet of Things (IoT) makes it more convenient to collect, transfer, and process the production data. As mathematical models and physical components of the intelligent equipment are highly complex, an early failure of complex equipment can then be predicted by data-driven monitoring and real-time diagnosis [4], [5].

The development of the EECG can be divided into four stages: data collection, health index (HI) construction, health status monitoring and division, and prediction of remaining useful life [6]. Table I provides the definitions of the key related terminologies. In [3], the framework guidance for automated data curation was given. Based on the continual basis, aggregated,

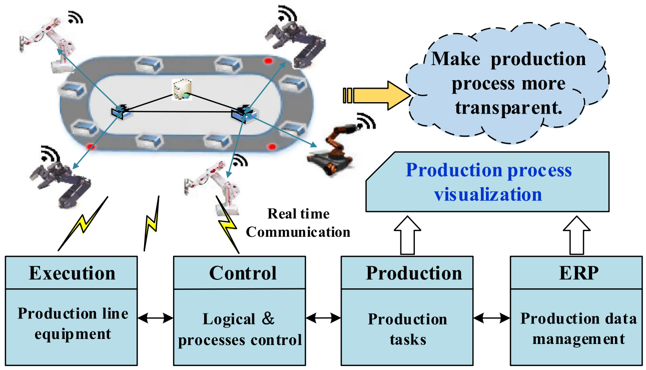


Fig. 1. Process visualization system model.

TABLE I
TERMINOLOGIES DEFINITION

Terminologies	Definition
Operation duration	The length of time that manipulator or other operation equipment lasts for completing a specific procedure.
Process duration	The length of time that a production process lasts. The process duration can be divided as several operation durations.
Cycle time	The length of time of a product repeatable process lasts for a product or a product's part. This can be applicable to production line or workstation.
Equipment beat	The time change that equipment is engaged in or waiting for a task. It can be regarded as an analogous to the heartbeat of EECG.
Production beat	Production line beat is used to split the spacing time and the working time of a workstation for the whole production line. Equipment (or workstation) beat can be regarded as its elements.

and effectively mined, Abid *et al.* [7] proposed a model-based fault detection and isolation method, and the concept of a fault severity index brings insight to identify the fault type and the severity level. Focusing on the dynamic slow decay process, Cao *et al.* [8] introduced the data-driven regression method to predict machining errors online. It is worth noticing that the real-time performance of the prediction model restrains model complexity. To address this, Traore *et al.* [9] built an auto-adaptive dynamic classifier to track slow degradation for dynamical systems' components with inductive analysis methods. This work showed that failure prevention of a key component by processing of sensors data can avoid a long downtime of the system. Among them, sensors or other measuring devices are more accurate in measuring certain aspects of the health condition of the equipment. The emerging tendency raises the higher demands for the safety, reliability, and maintainability of the manufacturing equipment. Thus, the performance degradation of the intelligent manufacturing equipment should be thoroughly analyzed. In this perspective, the operation duration may be a more comprehensive and a more intuitive indicator to reflect the operational state of the equipment.

Multicomponent equipment monitoring using fine-grained data is an advanced method for predicting the remaining useful life of the equipment [6], [10]. In [11], Rodrigues puts forward such a system to predict the remaining life based on performance indicators. This method relates the health factors of each component to the overall system performance. Similarly, prediction system of remaining useful life is performed by evaluating feature fitness by using deep neural network in [12]. The monotonicity and trend ability characteristics are closely related to the HI and timeliness restrictions. The operation duration of the intelligent equipment is an important indicator of the machine state. Moreover, the fluctuation of the operation duration can effectively reflect the performance degradation process in real time. The EECG system can provide a wide range of benefits to prediction of remaining useful life of the equipment.

Computer technologies have greatly enhanced data-driven operation and the maintenance mode in smart manufacturing [13]. For instance, Beet LLC built a process visibility system called enVision to provide real-time monitoring and process visualization for manufacturing equipment [14]. When the enVision system was applied to process visualization for a welding production line in a car plant, it proved that the system is effective in optimizing the cycle time by preventing unnecessary programming, excessive welding time, and some quality risks (e.g., explosive welding, and gun sticking). Different from the factory information system (FIS) that monitors the time from start to stop, enVision monitors the actual processes going on in between. However, the performance degradation monitoring of the manufacturing equipment is insignificant by using the process visualization. Furthermore, unreasonable division of the production beat will also affect the efficiency of the production line. Romero-Silva and Shaaban [15] pointed out that unbalanced average operation duration and buffer allocation would reduce the throughput of the production line. The extension work can be conducted, where the duration of the processes and operations of the intelligent manipulator will be optimized using mathematical planning methods, which can be helpful to improve the cycle time of the intelligent production line.

Compared with the aforementioned existing works, the main contributions of this article are as follows:

1) With the focus on performance degradation of the production line equipment, the EECG is built based on fine-grained data collection during the whole operation duration, which is useful for monitoring the health status of the manufacturing equipment in real time.
2) The implementation mechanism of the EECG is explained in detail, including division of the complete process duration into fine-grained time slots, vector-improved dynamic time warping (DTW) algorithm for time-series process matching, and other important working characteristics such as baseline, tolerance, and hotspot.
3) As for beat optimization of the intelligent production line and online monitoring of the equipment performance degradation, an optimization strategy of automatic production line EECG (APL-EECG) is proposed, to improve the efficiency of the intelligent production line and help

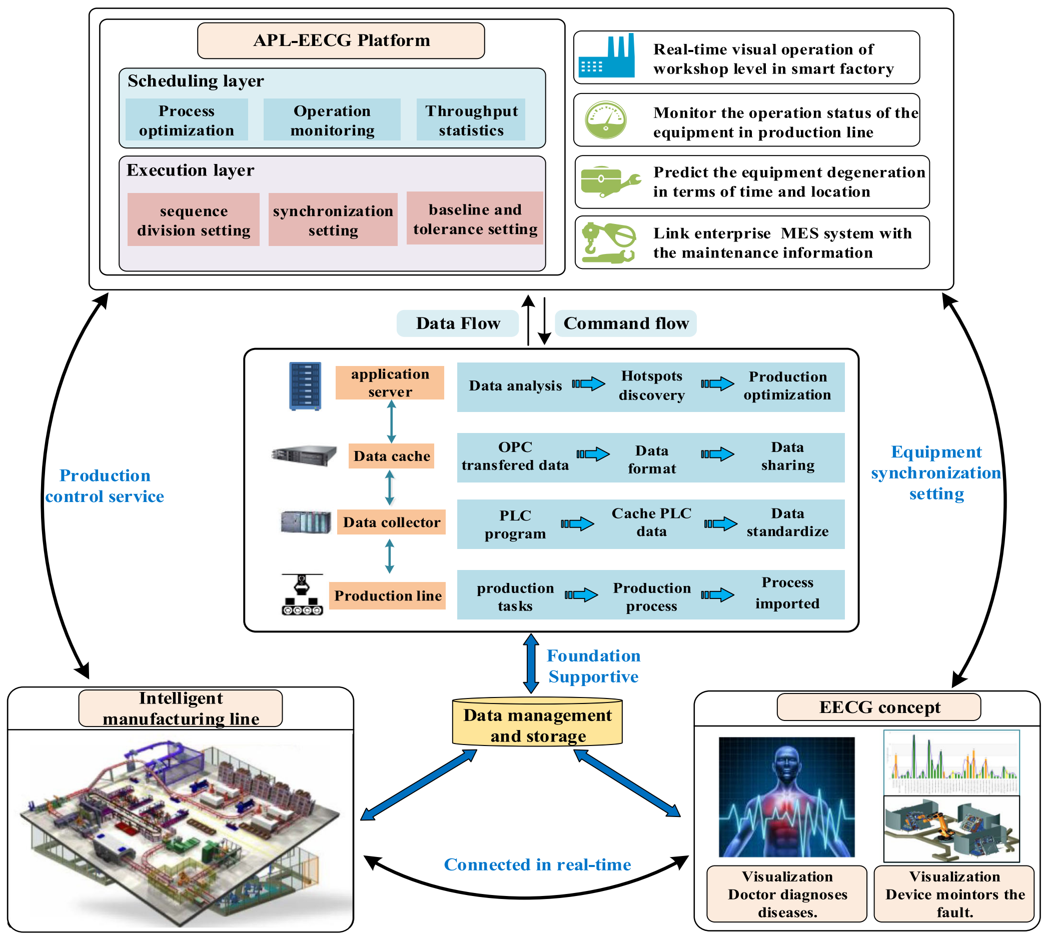


Fig. 2. System architecture of EECG in smart factory.

devise a preventive maintenance strategy for the intelligent equipment.

The rest of this article is organized as follows. Section II proposes the system architecture of the EECG and its role in smart manufacturing. Section III presents the implementation mechanism of the EECG including granular division of the process duration, matching strategy for process sequences, and several important operating characteristics. Section IV introduces the EECG-based performance degradation monitoring and production optimization for the intelligent production line. Section V implements the APL-EECG on a verification platform and analyses the experimental results. Section VI concludes this article.

II. System Architecture

The real-time acquisition of dynamic data information enables the EECG to monitor the operation status of an equipment and provide the time-series prediction of the equipment status. Fig. 2 shows the system architecture of the EECG for a mixed flow manufacturing production line in a discrete workshop. As shown in the figure, the architecture has three layers. First, the workshop automation network is utilized for data collection from the underlying equipment, including high-speed data collection by using programmable logic controller (PLC) and OPC UA-based data unified transmission. Second, the data server is used for format management, data caching, and data sharing. Last, the application server is deployed to provide the continuum analysis of the data, to explore the hotspots and further improve the production cycle. The EECG represents an intuitive visual display of data, which contributes to providing an in-depth perception of the equipment status. To build the APL-EECG, it is crucial to develop novel techniques based on the following aspects:

1) scientifically divide the granularity of the manufacturing process;
2) choose the online matching algorithm for time-series process sequences;
3) set the baseline for a single equipment to complete a process or a task; and
4) determine the tolerance degree for the fluctuation of the operation time.

The platform of the APL-EECG includes scheduling and execution layers, which are used for setting the parameters and optimizing the production, respectively. The EECG can clearly show the duration during the operation. Monitoring the operation status reflects the degradation trend of the equipment performance. It provides strong support for a new mode fault prediction. The APL-EECG realizes real-time process visualization

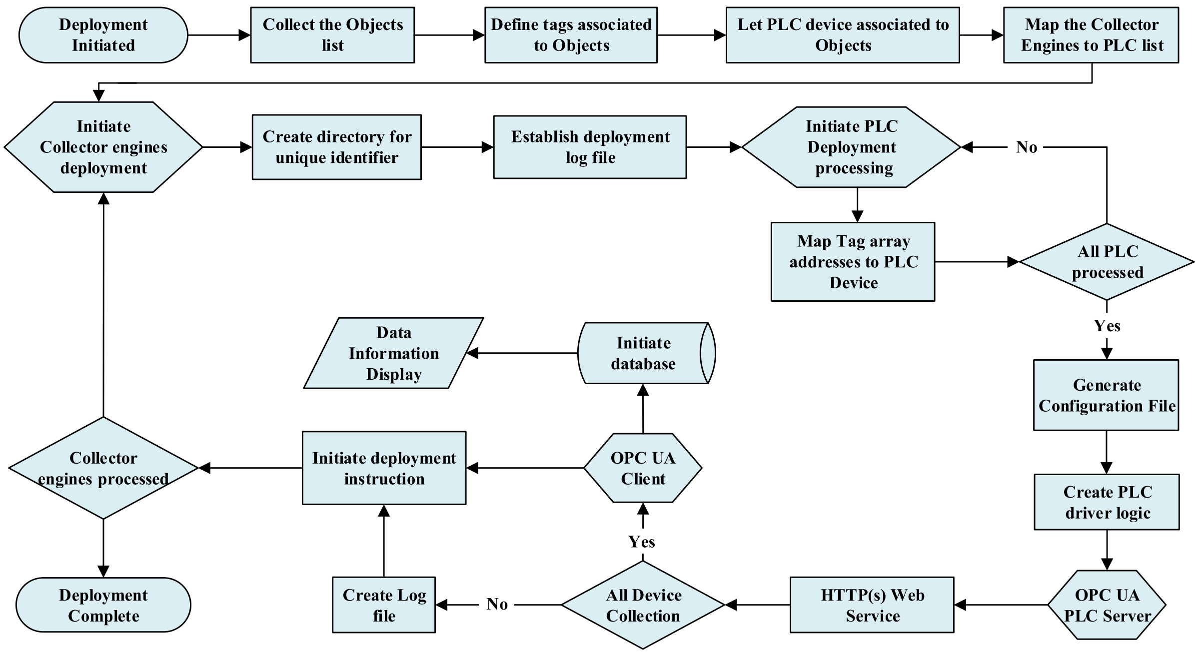


Fig. 3. Flowchart of data acquisition in APL-EECG.

in workshop and can be applied to a personalized customized production mode. With the operation status monitoring of the production line, the EECG can reveal the performance degradation and predict the evolution rule in terms of time, location, and degree. In this way, when the EECG is connected to the PLM or MES, it can provide preventive maintenance guideline for the workshop equipment.

III. Equipment Electrocardiogram Mechanism

The EECG monitors the operation status using the method of fine-grained processes visualization. Data acquisition from the equipment forms the basis of the EECG. Fig. 3 shows the flowchart of data acquisition processes in the APL-EECG. In discrete manufacturing, the production process of a workstation requires the equipment to complete the production task just in a small amount of the production time. The granularity division and fluctuation of the process duration are important EECG characteristics that can reflect a change in the equipment status. Considering these factors, this section mainly focuses on the EECG mechanism including the multigranularity division method, the matching strategy, and other work characteristics.

A. Granular Division of Process Duration

The time length of the operation duration forms the basis for building the EECG. The product manufacturing process is often subdivided into multiple processing tasks. There may be many processing tasks between the start and stop of a station, and each processing task can be further subdivided into one or more sequences. The raw data collected by PLC or by the equipment itself is the operation duration with time series feature. Rough set theory has the formal definition for the information system (IS) [16]. When it comes to the data collection based on multi-granularity, we were inspired by the rough set theory to define the EECG information system. In this section, we introduce the multigranularity division method based on the rough set theory.

Definition 1: EECG IS for a single equipment is represented by a four-tuple set $\mathrm{GRS} = (U, P, V, f)$, the IS of the APL-EECG can be described as

$$\mathrm{MGRS} = \{\mathrm{GRS}_i | \mathrm{GRS}_i = (U, P_i, \{(V_p)p \in ATi, f_i\})\}.$$

In this system, $U = \{e_1, e_2, e_3, \ldots, e_n\}$ denotes the nonempty finite object set of the equipment function, and it is also known as universe of the rough set. The process set denoted by $P = \{p_1, p_2, p_3, \ldots, p_m\}$ can be completed by the equipment function, while V_p denotes the cycle length of the process with $V = \cup_{p\in P} V_P$. The function $f : U \times P \to V$ is a mapping information function, and $f(e, p) \in V_p$.

Definition 2: $\exists p_i(t) \in P$, and $\forall e \in U$ constitutes $U = \{e_i | e_i(t) = \sum_{0\leq i\leq m} (\sim \hat{p}_i(t))\}$.

The cycle length of the operation duration for the ith process is denoted by $p_i(t)$. Based on the cycle length, the entire process is segmented, and the function of the equipment is divided into sequences of operations. The completion time of the equipment function depends on the total number of operation sequences.

Definition 3: Define that $f = \{f_i | f_i : U \times P_i \to V_{p_i}, \forall i \in div(T)\}$ is a mapping function and the process set P belongs to the function set U. The set $e = \langle (p_1, f(e, p_1)), (p_2, f(e, p_2)), \ldots, (p_n, f(e, p_n))\rangle$ shows that the total time consumed by a function is composed of times consumed by different operations.

The operation and nonoperation durations are divided according to the functional characteristics of the equipment. For noncontinuous operation equipment, such as the empty stroke of the equipment, the change of time length can be effectively captured, and the signal will not be lost when the network transmission channel is highly utilized.

Definition 4: Assume that the total time consumed by an equipment during a manufacturing process is $X_{\text{total}} = \sum_{i=1}^{N}\sum_{j=1}^{M} f(x_{ij})$, and the total operation duration is $E_p = \sum_{i=1}^{N} f(P_i)$, and then the efficiency of the granularity division of the equipment process can be represented by $\mu_p = \ln(\frac{E_p}{X_{\text{total}}-E_p})$. The channel utilization of the transmission network can be represented by$\mu_i = \frac{1}{MN}\sum_{i=1}^{N}\sum_{j=1}^{M} x_{ij}$.

In the preceding expressions, $x_{ij}$is the node of the operation division, and μ_p and μ_i are used to measure the granularity efficiency. The effective operation duration should be as long as possible according to the functional characteristics, so that $\mu_p > 0$. To avoid increase in the network load, the action interval of the equipment completing the process is ignored after the process is divided, such as the reset action of the manipulator during assembly and the empty stroke of the welding manipulator during welding.

The division of process duration is a complicated step. Definitions 1–3 give a general method to represent the structure of the EECG information, and Definition 4 gives a method to divide the process based on the functional characteristics of the equipment. The process division provides basic support for the determination of the subsequent cycle length.

B. Matching Strategy for Process Sequences

The EECG system accurately reflects the process progress in real time and meets the time critical requirements for anomaly detection. For an intelligent production line with variable mass customization, the product variety is changing in the running of the production line. The process sequences for the different product will change in real time. For the certain production categories, the processes sequences for the reference templates are collected in advance, and the reference templates are random selected from the collected process sequences. When the reference templates are known beforehand, the desired process will be matched with the reference templates online.

To identify templates of different processes, dynamic matching of the process template and real-time sequence of the time-series signal needs to be carried out in the EECG system. Inspired by the distortion measure in audio matching, we know that DTW is applied to measure the similarity of two voice sequences, in which Euclidean distance is used to calculate the distance between elements of sequences [17]. For the intelligent production line, the process flow is more complex. The elements of the matching sequence include station sequence and its process sequence. We use the matrix to represent the 2-D matching sequence. It is difficult to realize 2-D sequence matching by using Euclidean distance in the classical DTW method. Considering these factors, this section introduces a vector improved DTW algorithm [18] for developing the matching strategy. It exploits the time-series characteristics of the manufacturing process.

The DTW is used to compare the similarity of two sequences. The main idea behind this algorithm is to provide the optimal path for nonlinear alignment by minimizing the accumulated distance between the two similar sequences. Assume that Q is the test template, and C is the reference template. As shown in the following:

$$\begin{cases} Q = q_1, q_2, \ldots, q_i, \ldots, q_n \\ C = c_1, c_2, \ldots, c_j, \ldots, c_m \end{cases}. \tag{1}$$

DTW deals with the time-series sequences correspondence problem between Q and C by using the time normalization function, as shown in the following:

$$d_{i,j} = (x(i) - y(j))^2 \tag{2}$$

$$D = \min_{C} \frac{\sum_{n=1}^{K}\left[d(x_{i(n)}, y_{j(n)}) \cdot w_n\right]}{\sum_{n=1}^{K} w_n}. \tag{3}$$

In the abovementioned equation, $W = (w_1, w_2, \ldots, w_k, \ldots, w_K)$ denotes the warping path of the DTW. The minimum distance between the test template and reference template is given as$D$. It refers to the similarity of the two sequences.

The time-series sequences of the EECG system meet the preconditions of sequence matching by DTW, but these sequences have their particular features in production processes. Assume that a work piece in the whole production line is completed by S workstations and each workstation is composed of one or at most N processes. The mapping function $f: U \times P \to V$ denotes the operation duration, and when the number of the processes is less than$N$, the margin will be replaced by a zero value. The whole process is represented by a matrix of size $S \times N$, as shown in the following:

$$\text{FP} = \begin{bmatrix} f(e_1, p_{(1,1)}) & f(e_1, p_{(1,2)}) & \cdots & f(e_1, p_{(1,n)}) \\ f(e_2, p_{(2,1)}) & f(e_2, p_{(2,2)}) & \cdots & f(e_2, p_{(2,n)}) \\ \vdots & \vdots & \ddots & \vdots \\ f(e_s, p_{(s,1)}) & f(e_s, p_{(s,2)}) & \cdots & f(e_s, p_{(s,n)}) \end{bmatrix}. \tag{4}$$

Let $\gamma_i = (f(e_i, p_{(i,1)}), f(e_i, p_{(i,2)}), \ldots, f(e_i, p_{(i,n)}))$ as the ith row of the abovementioned matrix, and then (4) can be rewritten as $\text{FP} = [\gamma_1, \gamma_2, \ldots, \gamma_i, \ldots, \gamma_s]^T$. The production processes of the test templateFP_{test} and the reference template FP_{refer} can be expressed as follows:

$$\begin{aligned} \text{FP}_{\text{test}} &= [\alpha_1, \alpha_2, \ldots, \alpha_i, \ldots, \alpha_n]^T \\ \text{FP}_{\text{refer}} &= [\beta_1, \beta_2, \ldots, \beta_j, \ldots, \beta_m]^T. \end{aligned} \tag{5}$$

From the abovementioned equation, the estimated distance between two components of the test template and reference template is $d_{i,j} = \|\alpha_i - \beta_j\|^2$. It is defined as a component in the following:

$$D_{i,j} = d_{i,j} + \min \begin{cases} D_{i,j-1} \\ D_{i-1,j} \\ D_{i-1,j-1} \end{cases} \quad (2 \le i \le M, 2 \le j \le N). \tag{6}$$

The warping path $\phi_{(\alpha,\beta)}$ for the distance accumulation is determined by α_i and β_j, $\phi_{(\alpha,\beta)}(1) = (1,1)$and $\phi_{(\alpha,\beta)}(K) = (M, N)$. The step-length $\psi(k)$ is subject to the constraint $0 \le \psi(k) - \psi(k-1) \le 1$.

Algorithm 1: Vector Improved DTW Algorithm.

Input: $FP_{tset} = [\alpha_1, \alpha_2, \ldots \alpha_i, \ldots \alpha_n]^T$

Input: reference template set: $(FP^1_{refer}, FP^2_{refer}, FP^3_{refer}, \ldots, FP^l_{refer})$

Output: target reference template: $FP^{'}_{refer}$

Begin
    Initialization *//initialized test template;*
    for $i \leftarrow 1$ to l *//match every reference template;*
        $[1;K] \leftarrow [1;M] \times [1;N]$
        $\phi_{(\alpha,\beta)}(1) = (1,1); \phi_{(\alpha,\beta)}(K) = (M,N)$ *//alignment of sequence*
        ends; $\omega_k \leftarrow \phi_{(\alpha,\beta)}(k)=DWT(\alpha_x(k), \beta_y(k))$ *//calculate the weight;*
        for $n \leftarrow 1$ to K
            $d(\alpha_{x(n)}, \beta_{y(n)}) = \|\alpha_{x(n)} - \beta_{y(n)}\|^2$
            $Sum(D_n) = Sum(D_{n-1}) + d(\alpha_{x(n)}, \beta_{y(n)}) \cdot w_n$ *// w_n is the weighting funication*
            $Sum(W_n) = Sum(W_{n-1}) + w_n$
        end for
        $Dist(FP_{test}, RP^i_{refer}) = Sum(D_n) / Sum(W_n)$ *//calculate the similarity;*
    if $Dist(FP_{test}, RP^{i-1}_{refer}) \geq Dist(FP_{test}, RP^i_{refer})$
        target reference template: $FP^{'}_{refer} = FP^i$
        return $FP^{'}_{refer}$
    end if
End

The matching strategy for the process sequences can be summarized as follows. When the production sequences of the equipment are collected by the APL-EECG, the matching strategy is adopted for template identification. The distance between the test template and each reference template presented in the template library is calculated. The shortest distance indicates the highest similarity of the production sequence. The most similar template is chosen for real-time alignment of the time-series sequences. Algorithm 1 shows the vector improved DTW algorithm.

C. Important Operating Characteristics

The matching strategy for the process sequences ensures the alignment of sequence in the acquired time-series data. The length rulers of the production sequences are needed to evaluate the acceptability of the operation duration. The baseline represents the expected or designed duration of each operation, and the tolerance represents the floating value of the baseline after the baseline is determined. When the baseline and tolerance are set up, the operation duration is graded into either of the four levels: good, warning, warning, and fault. The determination of the baseline and tolerance is closely related to the time length of the operation duration. This section presents the theoretical basis of these operating characteristics for the APL-EECG.

The baseline is used to demarcate the expected cycle length of the process, and it is also a base-value to measure the normality of the equipment beat. We use the sampling statistics to calculate the base-value of an operation duration. The root mean square (RMS) value of the sampling data is adapted as the base value. Equation (7) reflects the cycle length of the sampling process of a random *N*th times. The cycle length of the *i*th sampling in the process *j* is given by $p_j^{(i)}$, and U_{BL} represents the base value of a process in EECG as

$$U_{\mathrm{BL}} = \sqrt{\frac{\sum_{i=1}^{N} [f(e, p_j^{(i)})]^2}{N}}. \tag{7}$$

Tolerance is closely related to the operation duration. It is the benchmark for judging whether the equipment beat around the baseline is within a normal range. The modified sample variance is used to express the tolerance of the operation duration offset baseline, as shown in the following:

$$S_n^* = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} \left(f(e, p_j^{(i)}) - U_{\mathrm{BL}}\right)^2}. \tag{8}$$

In the abovementioned equation, S_n^* represents the tolerance value for fluctuation of the operation duration. The operation duration is graded according to the tolerance value. A serious deviation of a normally operating equipment from the baseline is a small probability event. According to the long-term sampling observations, the change of the operation duration follows a normal distribution. In this part, the 3σ principle is used to evaluate the fluctuation of operation duration and $\sigma \approx S_n^*$.

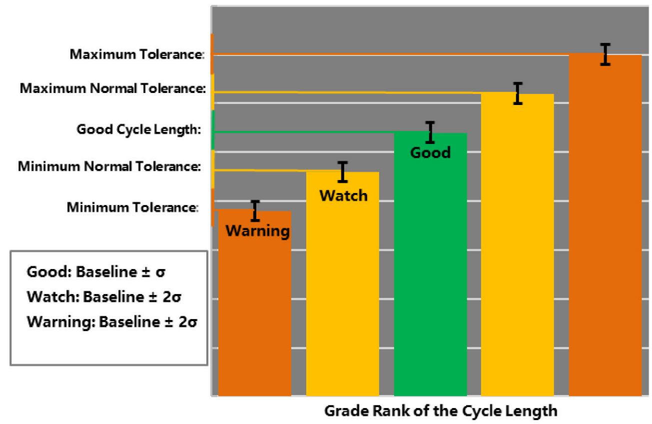


Fig. 4. Grading of the cycle length based on tolerance.

As shown in Fig. 4, the *X*-axis reflects the graded for adjusting the values of the cycle length. The *Y*-axis reflects the tolerance value based on the 3σ principle. The grade division of the *X*-axis is accompanied with the changing tolerance value of the *Y*-axis. When the operation duration is within the baseline tolerance, it will be marked as "good." The time length higher than the baseline tolerance will be marked as "watch," while that higher than the "nTol" value will be marked as "warning." When the operation duration is higher than the "Tol" value, it means that the equipment would malfunction.

In the APL-EECG system, the envelope is an important feature that reflects the floating range of the operation duration. It directly represents the extent to which the operation duration exceeds the baseline, and the value is calculated according to (9). In the following equation, U_{Evp} denotes the limiting value of the envelope:

$$\begin{cases} U_{\text{Evp}} = U_{\text{BL}} \pm \min \sqrt{\sum_{m=1}^{k} \left(\frac{f(e, p_j^{(m)}) - f(P_J)}{f(P_J^{(\max)}) - f(P_J^{(\min)})} \right)^2} \\ j \neq 1, j \in P_J \end{cases} . \tag{9}$$

Under random sampling carried out k times $P_J = (p_1, p_2, p_3, \ldots, p_J)$ and $f(P_J)$ denotes the sampled value. In this work, the higher limit of the envelope is adopted.

IV. Performance Monitoring and Production Optimization Using EECG

A. Automatic Production Line—EECG Optimization of Cycle Time

The cycle time mainly determines the production rate of the intelligent production line. The operation performance of the equipment and logical settings of the operation instructions significantly impact the cycle time. In the welding production line of a car plant, the factors that can delay the equipment beat include inefficient waiting area, unreasonable interference area, loosening of clamping equipment, fluctuation of welding manipulator, and aging of equipment sensors. The APL-EECG can effectively reflect the change in operation duration, and then quickly identify the action steps to improve the operation cycle time.

Using the APL-EECG, the method of mathematical programming is adapted to optimize the cycle time. When the equipment executes an external task, the collection of the equipment beat can be regarded as the sequence flow of the process. The entire cycle time is composed by the work piece delivery time and the processing time. The operation duration will be reflected in the APL-EECG in a fine-grained fashion.

The mathematical optimization model of the cycle time in the APL-EECG is given in the following:

$$\min Z = \sum_{i=1}^{m} \sum_{j=1}^{m} x_{ij}(c_{ij} + o_{ij})$$

$$\text{s.t.} \begin{cases} \sum_{i=1}^{m} x_{ij} = 1, i = 1, 2, \ldots, m, \\ \sum_{j=1}^{m} x_{ij} = 1, j = 1, 2, \ldots, m, \\ \sum_{i=1}^{s} \sum_{j=1}^{s} x_{ij} \leq s - 1, 2 \leq s \leq m - 1, \\ \quad s \subseteq \{1, 2, \ldots, m\} \\ x_{ij} \in \{0, 1\}, i, j = 1, 2, \ldots, m, i \neq j \end{cases} \tag{10}$$

The optimization target is to minimize the operation duration and choose the appropriate conveying path of the work piece. It also makes the task execution sequence more compact when building the APL-EECG. In (10), the production task set is $T = \{t_1, t_2, \ldots, t_m\}$, and the operation instructions depend on the type of this task set. The transmission path of the work piece between stations *i* and *j* is denoted by c_{ij}, which is limited by the conveying path of the actual production line. The time consumed on the station is given by o_{ij}, and x_{ij}denotes that task t_i will be executed after the execution of task t_j, and also represents the direction in which the tasks continue. A global optimization algorithm used for solving (10) is given in Algorithm 2.

Algorithm 2: Global Optimization Algorithm for Solving (10).

Input: key sequence value $x_{ij}^o \Rightarrow c_i \rightarrow c_j$;
Task Set $T \subseteq$ *Command Set C*
Output: the optimal solution $x_{ij}^* \Rightarrow c_i \rightarrow c_j$

Begin
  Initialize the unknown sequence x_{ij}^o
  for $k \leftarrow 1$ to K *//K denotes the alternative operation sequence*
    select the feasible value $x_{ij}^{(k)} \in x_{ij}^o$
    for $i \leftarrow 1$ to m *//upgoing command value*
      for $j \leftarrow 1$ to m *//downgoing command value*
        $x_{ij}^{(k)} \Rightarrow c_i \rightarrow c_j \parallel T \subseteq C^{(k)}$
        $Z^{(k)} = Z^{(k)} + x_{ij}^{(k)}(c_{ij} + o_{ij})$ *//calculate the Z value*
      end for
    end for
    If ($Z^{(k)} \leq Z^{(k-1)}$) then *//loop through to get the minimum*
      $Z^{\min} = Z^{(k)}$
    end if
  end for
  return $x_{ij}^* \rightarrow Z^{\min}$ //return the optimized sequence
End

B. Online Monitoring of Equipment Performance Decay

Healthy operation of intelligent equipment is a guarantee for the highly efficient production line. Traditional FIS has a single early warning mode, which only records early warning events corresponding to a finite number of time nodes. Thus, it is highly likely to lose a number of important event alarms. The APL-EECG system can continuously monitor the equipment performance decay and help predict the potential failure trend of the equipment visually. Changes in the continuous state are judged by the boundary condition. Deviation from the normal excessively or repeatedly will be marked as hotspots.

In terms of future performance degradation of the intelligent equipment, the APL-EECG adopts a grading scheme based on the emergency level. Fig. 5 reflects the online monitoring of equipment performance decay for several processes in the production line. The upper side of the horizontal axis shows the cycle length of a process, and the upper envelope gives the range of the cycle length that can be floated upward. The lower side of the horizontal axis shows the grading level used for the cycle length evaluation. Those processes that are continuously graded as "warning" will be also labeled as hotspots. Hotspots are important references for developing effective preventive maintenance strategies for the equipment. During operation of the production line, the performance of the equipment decays continuously. The online alarm mode of the APL-EECG can directly reflect the increase of the operation duration and accurately locate the source of an upcoming future performance degradation.

V. Implementation of EECG

A. Implementation Scenarios

An intelligent production line is established in our intelligent manufacturing laboratory. It involves workpiece carving and

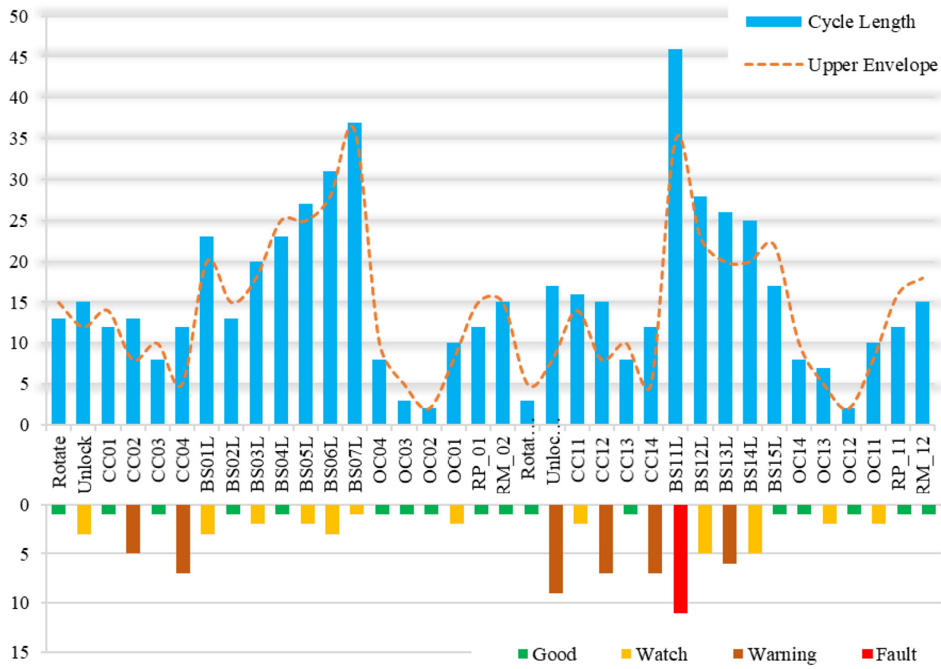


Fig. 5. Online monitoring of equipment performance decay.

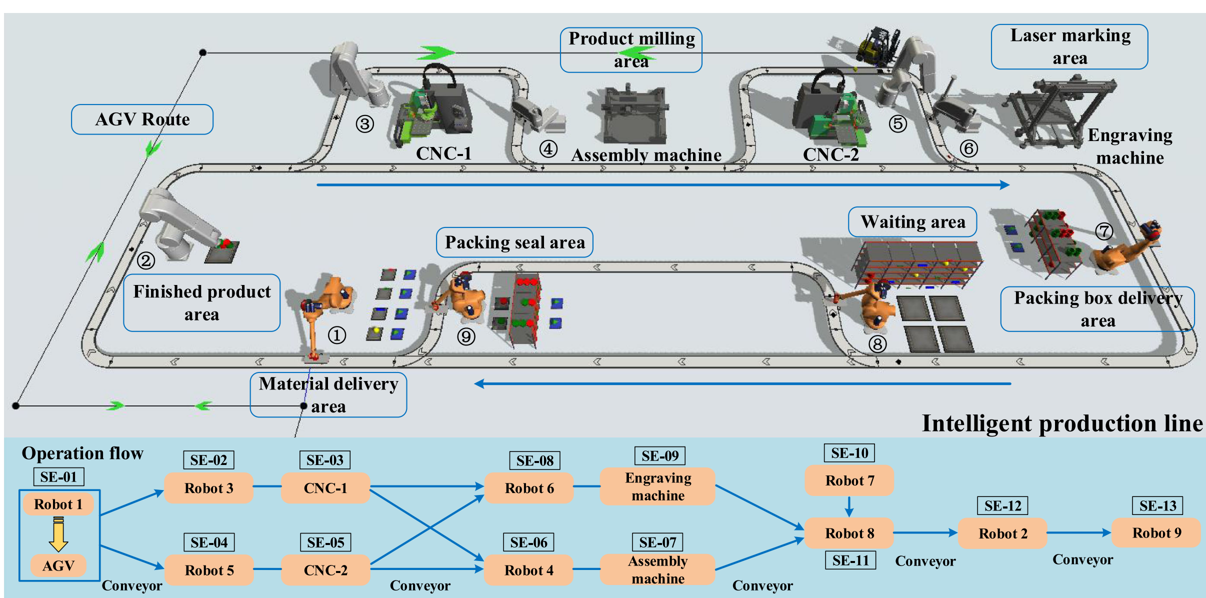


Fig. 6. Implementation platform of the APL-EECG in the manufacturing laboratory.

assembly, and patterns laser marking. The production line is a typical small batch discrete production line. The layout of the production line in the laboratory is shown in Fig. 6. The production stations are distributed discretely between the main line and the branch line, and RFID tags are used to store the operation information. The workpiece is transferred by the conveyor belts or AGV continuously.

In this section, the implementation platform of the APL-EECG is described, which was deployed based on our application scenario. As shown in Fig. 6, every execution unit is deployed as the workstation of EECG, which can be divided into 13 sequences (SE) including nine manipulators, two CNCs, a marking machine, and an assembly machine. The inherent beat of each equipment is tested in advance because the operation times of different types of products vary greatly. For the testing purposes, the type of products processed by CNC or engraving machine is determined. The beat of the main working station is listed in Table II. The main validation schemes are listed as follows:

1) deployment of the APL-EECG;
2) improvement of the equipment beat;
3) performance degradation monitoring of the equipment; and
4) maintenance guidance for the production line.

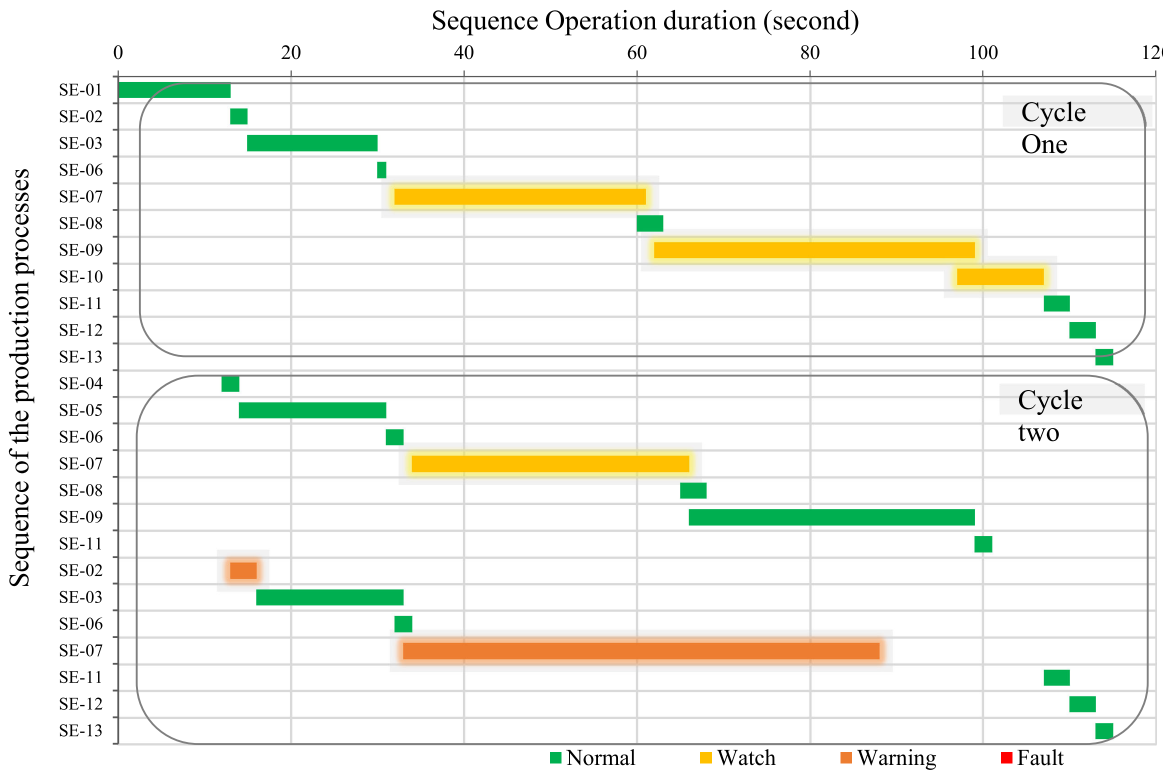


Fig. 7. Experimental results obtained from the APL-EECG platform.

TABLE II
BEAT OF THE MAIN WORKSTATIONS

Workstation	Minimum beat	Average beat	Beat std
Robot 1	2.3	3.5	1.7
Robot 3	1.2	2.3	0.9
Robot 5	2.4	3.7	1.3
Robot 8	3.1	4.6	1.3
Robot 9	3.2	5.1	1.6
CNC-1	35.2	52.7	14.5
CNC-2	32.7	50.6	15.3
Assembly Machine	28.6	42.7	20.3

B. Implementation Results

This section shows the performance of the APL-EECG implementation based on the existing prototype platform. Tests were carried out over the duration lasting more than 90 days.

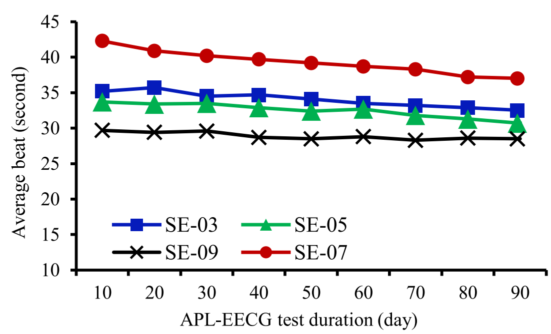
Adjacent operation cycles showing large variation of the cycle length are selected to reflect the production process of two different products, as shown in Fig. 7. The figure shows that the cycle length of the *SE-07* increases continuously and exceeds the minimum tolerance. Its grading information changes from "watch" to "warning," and consequently, its dynamic state will be displayed in the maintenance interface as a hotspot. The cycle length of *SE-02* shows large fluctuations, which reflect the instability in its operation.

Table III lists parts of the alarm information of the APL-EECG. The table reflects the increase caused by aging equipment components in the operation duration. Based on the maintenance information of *SE-03*, its process changes from the "over cycle" and "blocked internally" to the final "blocked down" state. This demonstrates that the EECG platform can provide continuous monitoring information. Eventually, it was discovered that the "blocked down" state was caused by the damage to manipulator caliper. As the traditional FIS is based on the timed feedback or manual operation, it is difficult to guarantee all-round relevance of the equipment status. The FIS does not reflect the decay process of the equipment but only its final status. On the contrary, the APL-EECG can provide continuous alarm information according to the fluctuation of the cycle length. Therefore, the APL-EECG can help in developing a reasonable maintenance strategy to avoid sudden "blocked down" state of the equipment.

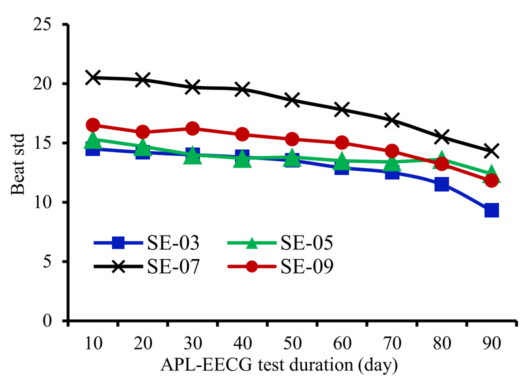
Based on Section IV.A, it can be seen that the deployment of the APL-EECG can provide the fine-grained operation status of the equipment and optimize the cycle time by using the mathematical programming methods. From the aspect of workstation, the delay can be reduced after the dwell time is reduced. In the early stage, the unreasonable program setting can be detected intuitively on the EECG panel. Aging components of the equipment may increase dwell time during the operation. For example, if loosening and clamping of a part are checked simultaneously, tightening of the part can be accelerated, and the time between tightening and loosening can be reduced. From the aspect of mathematical planning, the information of workstation or manipulator that the action synchronization,

TABLE III
ALARM INFORMATION OF THE APL-EECG

Time	Sequence	State	Duration	Status alert	Hotspot	Maintenance Assist
Tues. 15:07:13	**SE-03**	**Over Cycle**	**46 s**	**Watch**	**No**	**No**
Tues. 16:08:43	SE-02	Over Cycle	5 s	Watch	No	No
Wed. 09:12:55	SE-08	Over Cycle	7 s	Watch	No	No
Wed. 11:23:15	**SE-03**	**Internal Blocked**	**52 s**	**Warning**	**Yes**	**No**
Wed. 15:09:20	SE-04	Over Cycle	5 s	Watch	No	No
Wed. 15:30:32	SE-01	Out of Auto	53 s	Warning	Yes	Charging
Wed. 17:27:08	SE-09	Over Cycle	72 s	Warning	Yes	Tool Change
Thur. 09:21:07	SE-11	Over Cycle	18 s	Watch	No	No
Thur. 10:14:32	SE-02	Over Cycle	5 s	Watch	No	No
Thur. 15:07:23	**SE-03**	**Internal Blocked**	**50 s**	**Warning**	**Yes**	**No**
Thur. 16:20:17	SE-13	Over Cycle	8 s	Warning	Yes	No
Fri. 10:23:31	SE-01	Over Cycle	63	Watch	No	No
Fri. 13:35:12	SE-04	Internal Block	12 s	Warning	Yes	Replace valve
Fri. 15:42:55	**SE-03**	**Blocked Down**	**127 s**	**Fault**	**Yes**	**Caliper replacement**
Mon. 11:17:23	SE-13	Internal Blocked	17 s	Warning	Yes	Fixture Change



(a)



(b)

Fig. 8. Optimization effect of the APL-EECG on cycle time. (a) Average beat. (b) Beat std.

program action, and interference area can be optimized will feedback to the operation and maintenance system. Fig. 8 shows the optimization effect of the APL-EECG on the cycle time in our prototype platform. Fig. 8(a) demonstrates that the average operation duration of the four processes is gradually decreasing. From Fig. 8(b), it is evident that the standard deviation of the four processes is gradually decreasing, which indicates increasing stability of the equipment.

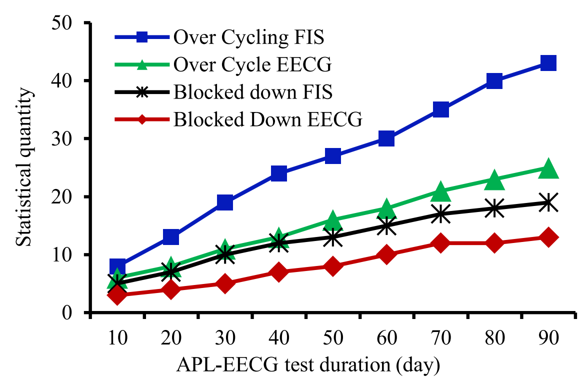


Fig. 9. Comparison of the performance of the FIS and APL-EECG over the complete test duration.

During the 90 days test, the number of times "over cycle" and "blocked down" occur in the APL-EECG system are counted. Under a typical FIS, the monitoring of the production line would be limited to see when a cycle has started and stopped through the cycle time. APL-EECG monitors the time from the start to stop and monitors the actual underlying processes during the cycle. Compared with the FIS, Fig. 9 shows that the APL-EECG can effectively reduce both "over cycle" and "blocked down" counts, and the results show that the APL-EECG can improve the continuity of the intelligent production line.

In the experimental results, we selected a wide range change of the cycle time to demonstrate the effect of implementing the APL-EECG. Practically, the cycle time of the production line is usually measured in seconds for automobile or packaging. Even a slight improvement of the equipment beat has the potential to increase the production line efficiency and bring huge economic benefits for enterprises. The equipment beat can be optimized by reducing the dwell time or modifying its unreasonable procedure settings. Considering the long life cycle of the equipment, the test on the equipment itself is not significant when most of the test data are normal. Because most intelligent equipment ages gradually, the APL-EECG can effectively monitor the operation status of the equipment in the long run and identify potential faults in the equipment.

VI. Conclusion

To address performance degradation of the equipment, this article introduced an EECG mechanism for operational maintenance in an intelligent production line. The EECG can present real-time operation status of the intelligent equipment visually. The proposed APL-EECG can present the current equipment state, its state in the near-future, and various means to improve its health status. A long-term test in laboratory settings showed that the APL-EECG system could monitor the operation status of the equipment in real-time and effectively improve the cycle time of the intelligent production line. Moreover, the APL-EECG can help identify the performance imbalance of the manufacturing equipment in advance. For future work, we will extend the fault identification of the equipment to predict its remaining useful life using the EECG.

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