Non-intrusive Condition Monitoring for Manufacturing Systems

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***Abstract*—A non-intrusive method for monitoring conditions in manufacturing systems is proposed. The method requires only a single current sensor for the monitoring of multiple machine individually, which is done by means of disaggregating measured waveforms. For accurate disaggregation even in complicated systems with multiple identical machines, it employs a new model-combining factorial hidden Markov model (FHMM) with behavioral models derived from queuing theory. Experimental results with an actual system show that the proposed method achieves more accurate disaggregation than conventional methods and obtains such valuable information on productivity as the reasons for and timing of manufacturing process stoppages.**

Keywords—non-intrusive monitoring; factorial hidden Markov model; queueing network

I. Introduction

Improvement in production efficiency has been a central issue in the manufacturing industry, and theoretical approaches toward it have been considered, e.g., queuing theory [1]–[3], cellular automata [4], and simulation-based optimization [5]. While these approaches can be useful in the exact analysis of a manufacturing system, their theoretical models assume that a large number of parameters related to the actual state of the system will be known. Such parameters are, however, unavailable in practical applications.

Data-driven approaches have also been studied [6]–[9] to analyze the states of systems on the basis of data collected from sensors or machine logs. However, most of these methods require installing sensors and/or communication devices for data acquisition, which would be unacceptable in many cases. This paper focuses on a family of monitoring methods that uses only one electrical current sensor for multiple machines in manufacturing systems.

Non-intrusive load monitoring (NILM) [10]–[13] is a powerful technique for this purpose. It monitors the individual electrical power consumption of multiple machines by means of only one sensor placed on the main power supply line and extracts useful features from a time sequence of power consumption and current waveforms. For home appliances, such methods as integer programming (IP) [11] and factorial hidden Markov models (FHMMs) [12, 13] are applied to this task, assuming that appliances can be represented as combinations of binary (on/off) state models. However, those models are not suitable for manufacturing-machines because the mechanical workings of such machines are much more complex than those of home appliances. Further, in many systems, a number of identical or similar machines are located in a single production line and are connected to the same power line. As those machines produce very similar current signals, it is difficult to identify individual machines and to estimate individual states.

There are two types of approaches in NILM: *supervised* [10, 11] and *unsupervised* [10, 12, 13]. This paper focuses on unsupervised methods, for which there is no need to provide preliminarily training waveform data for individual machines (a requirement with supervised methods).

In this paper, we propose an unsupervised non-intrusive monitoring method that is applicable to complex manufacturing systems and uses a single current sensor. It employs a behavioral model derived from theoretical analyses of manufacturing systems (i.e., using queuing theory) into an FHMM to improve accuracy in disaggregating current signals in complex systems. Further, as the model is highly interpretable, it makes it possible to visualize flow in manufacturing processes and to obtain valuable information, such as the reasons for and timing of manufacturing process stoppages. To the best of our knowledge, the method proposed in this paper is the first attempt at NILM that is applicable to complex manufacturing systems.

This paper is organized as follows: Sec. 2 describes a target system that we focus on, Sec. 3 briefly summarizes previous methods and problems in applying them to the system, Sec. 4 describes our proposed method, Sec. 5 gives experimental results, and in Sec. 6, we summarize our work.

II. Target System

We focus on manufacturing systems that have the following features: (i) a number of similar machines are employed, (ii) each machine has sequential processes that are more complex than the switching of on/off states, and (iii) the machines are automated and change their states in accord with both internal states and such external factors as system errors or the lack or jamming of products in the system. Fig. 1 shows an example setup for a surface-mounting system that we have used in a series of experiments. In this system, electronic parts are mounted and soldered on printed-circuit boards (PCBs). The line is composed of a printing machine, three mounters, a reflow furnace, two inspection machines, and conveyor belts connecting them. We

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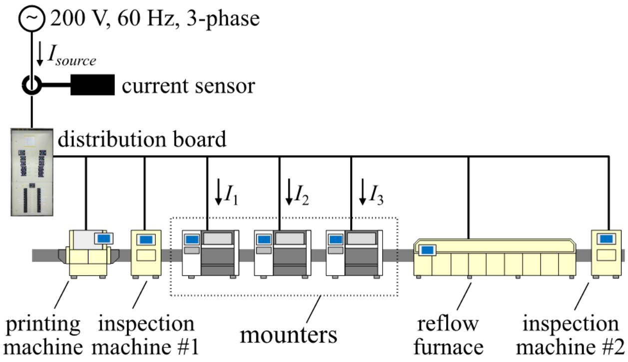

Fig. 1: Example setup of a manufacturing system.

focus on the mounters because they represent the most time-consuming process, i.e., they are a kind of bottleneck in the line. We placed a current sensor on one of three transmission lines from a three-phase power supply in order to measure the current waveforms for the system as a whole.

Our goal here is to disaggregate the current signals at the main line I_{source} into signals for individual mounters I_1, I_2, I_3 and then to estimate conditions with respect to them. The biggest difficulty is that the mounter waveforms are quite similar because they are from the same type of machine.

III. Conventional Methods

FHMMs have been used in conventional methods for unsupervised NILM applied to home appliances [12, 13] for which overall power consumption was disaggregated into individual appliance consumption levels, and their binary (on/off) states were simultaneously estimated.

Conventional methods cannot be applied usefully in manufacturing systems, however, because manufacturing-machines often have waveforms that are too similar to distinguish among. In the case of the system shown in Fig. 1, the mounters are of the same type and have very similar waveforms, which would result in inaccuracy with conventional methods.

Further, current signals in manufacturing systems are more complex than those of home appliances. They continuously change as manufacturing proceeds, unlike signals in home appliances, which are stationary most of the time. This means that signals should be represented by FHMMs that feature sparse and structured transition matrices. These would be hard to learn, however, because sparseness and structure in a transition matrix would result in lower likelihoods under the assumption of the 1st-order Markov property made for ordinary unconstrained FHMMs. This means that effective constraints would be required for the models' transition matrices to be effective.

IV. Proposed Method

To avoid the problem discussed above with respect to conventional methods, we propose an FHMM-based model combined with constraints derived from domain knowledge, i.e., machine behavior as explained with queuing theory. The constraints form a deterministic structure in the transition matrices. The structure enables learning appropriate temporal

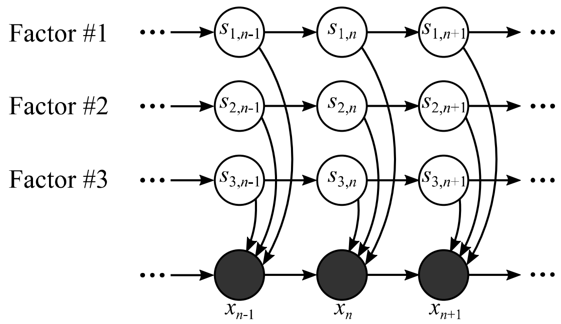

Fig. 2: Factorial Hidden Markov Model.

waveform patterns. As these temporal patterns are specific not only for machines but also for their individual mechanical workings, our method is able to distinguish among individual machines even of the same type.

In this section, we first introduce an ordinary unconstrained FHMM and then introduce behavioral models for manufacturing-machines and combine them into an constrained FHMM. After that, we explain how to use the model to disaggregate waveforms.

A. Factorial Hidden Markov Model

A factorial hidden Markov model (FHMM)[14] is an extension of an HMM that has a set of hidden states for each of K independent factors (Fig. 2). FHMMs are used for such unsupervised learning problems as those for NILM [12,13]. This paper assumes that individual factors represent individual machines in a manufacturing system. Here, each of K machines has M states, the state of the k-th machine at a time n ($= 1, \cdots, N$) is $s_{k,n}$, and its signal (i.e., electrical current) is determined by its state: $x_n^{(k)} = \mu_{s_{k,n}}^{(k)}$. According to the Markovian property of FHMM, the state of an individual machine is determined stochastically by transition matrices:

$$A_{i,j}^{(k)} := P\left(s_{k,n} = j \middle| s_{k,n-1} = i\right). \quad (1)$$

Let us consider an *additive* FHMM in which observation $X = (x_1, \cdots, x_N)$ is represented as a summation of signals of all factors with Gaussian noise ε of variance σ^2:

$$x_n = \sum_{k=1}^{K} x_n^{(k)} + \varepsilon. \quad (2)$$

In the next section we employ a behavioral model for manufacturing-machines, in order to introduce constraints into the ordinary FHMM described above.

B. Behavioral Model of Manufacturing-Machines

We employ a behavior model, derived from the queuing theory, for manufacturing-machines. We start from an open queuing network [1], as shown in Fig. 3. Work-in-progress (WIP) products flow through a manufacturing system. Each machine in the system performs a single manufacturing process, such as cutting, assembling, testing, or packing, during a time period T. Conveyor belts between machines act as buffers receiving WIP products from preceding machines and supplying

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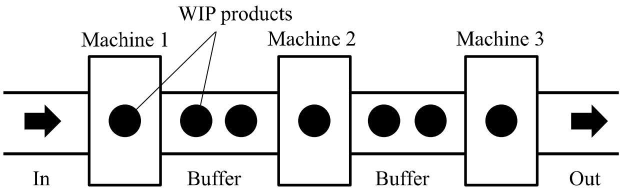

Fig. 3: Open queuing network.

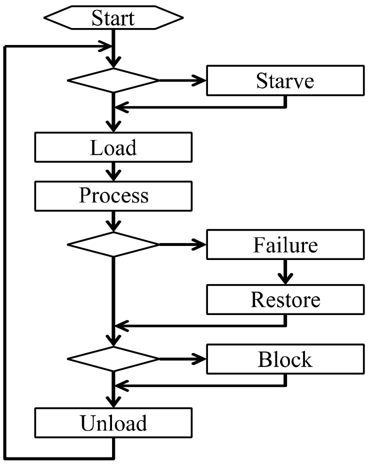

Fig. 4: Flow chart for behavioral model of a manufacturing-machine.

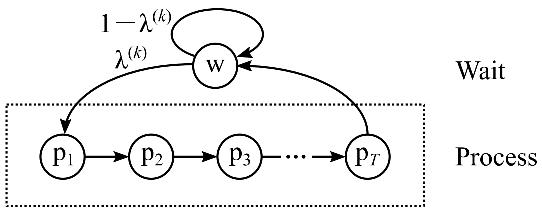

Fig. 5: State transition for a simplified behavioral model.

them subsequent machines in a first-in-first-out manner. An empty will have nothing to supply to a subsequent machine, and a full buffer will be unable to receive anything from a preceding machine; in such cases, operations will stop. Fig. 4 shows a flowchart for such a system. When the system is working properly, a machine will repeat sequential movements: importing a WIP product (Load), doing a manufacturing process (Process), and then discharging the product (Unload). If its input buffer becomes empty and unable to supply WIP products (Starve) or its output buffer becomes full and unable to receive products (Block), the machine will wait until the situation is resolved. If a process fails because of an error (Failure), the machine will wait until operators fix the problem and normal operations are restored (Restore).

To use such a behavioral model efficiently in the FHMM, we first employ an approximation of the model. In the approximation, Load and Unload are merged into a part of the Process state, Restore is omitted in consideration of the very short durations, and Starve, Block, and Failure states are merged into a single state (Wait; "w"). Additionally, the correlation between individual buffers and machines is ignored, so that the buffers can be treated as a "mean-field" that supplies and receives WIP products in accord with a simple Poisson process with intensity parameter $\lambda^{(k)}$. Finally, we obtain the simplified model shown in Fig. 5. Machine power consumption remains nearly constant during Wait-state idling. Conversely, power consumption in the Process state will change with a definite sequence of manufacturing processes of length T. We expand this deterministic process into a one-way series of states "$\mathrm{p}_1, \cdots, \mathrm{p}_T$," at each of which we can assume constant power consumption. The resulting transition-matrix constraints shown in Fig. 5 are:

$$A_{i,j}^{(k)} = \begin{cases} 1 \quad , & (i,j) = (\mathrm{p}_t, \mathrm{p}_{t+1}), (\mathrm{p}_T, \mathrm{w}), \\ \lambda^{(k)} \quad , & (i,j) = (\mathrm{w}, \mathrm{p}_1), \\ 1 - \lambda^{(k)}, & (i,j) = (\mathrm{w}, \mathrm{w}), \\ 0 \quad , & \text{otherwise}. \end{cases} \tag{3}$$

While a model with these state transitions is a subclass of an FHMM, it is likely to be more suitable to manufacturing-machines than would be an unconstrained FHMM because the one-way structures of the model are capable of learning long-term waveform patterns that are only slightly different, even among machines of the same type.

C. Inference Methods

As the proposed model is a type of FHMM with certain constraints, several methods, such as variational and sampling approaches, are available for unsupervised learning [13-14]. We employ the structured variational (SV) method introduced in [14] because sampling methods suffer from serious slowdown in convergence owing to the constraints' creating a high correlation between hidden variables along the time axis. Note that the sparseness of the transition matrices ($T + 2$ non-zero elements) in the model further speeds up the matrix-vector multiplications that appear in the forward-backward algorithm in the SV method and keeps calculation time down to $O(NKM)$ for each iteration, whereas an unconstrained FHMM would require $O(NKM^2)$.

Once unsupervised learning processes have been completed, i.e., the parameters $A^{(k)}, \mu^{(k)}, \sigma^2$ and the posterior probabilities of hidden states have been estimated, the disaggregated current signal of each machine is calculated as follows:

$$x_{\mathrm{est},n}^{(k)} \coloneqq \mathbb{E}\left[x_n^{(k)} \middle| X\right] = \sum_{m=1}^{M} \mu_m^{(k)} P\left(s_{k,n} = m \middle| X\right). \tag{4}$$

V. Experimental Results

A. Measurements and Preprocessing

We placed a current sensor on the power supply line of the system, as shown in Fig. 1. Fig. 6 shows an example of the current waveform (I_{source}) at the power supply line of the system. The current signal had a basic frequency of 60Hz, the commercial frequency of the power grid, and its amplitude and waveform changed continuously, mainly as a result of the mounters' moving their mounting heads shuttle-wise very

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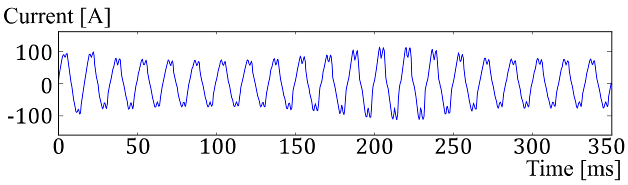

Fig. 6: Current waveform I_{source} measured on main supply line.

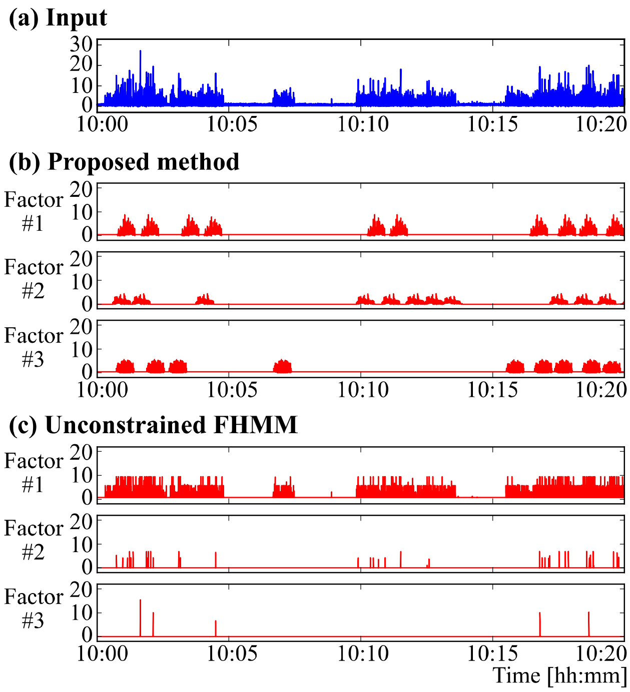

Fig. 7: (a) Preprocessed input current signal. (b), (c) Disaggregated signals estimated by FHMM with behavioral model (proposed method) and unconstrained FHMM, respectively.

quickly between parts feeders and PCBs. As has been noted in Sec. 2, we focus here on the disaggregation of the three mounters. We applied two simple signal processing techniques to avoid the extraction of signals from machines other than the mounters. Applying a high-pass finite impulse response (FIR) filter to source current signal I_{source} and taking root-mean-square (RMS) values of that for every 100 milliseconds, we were able to extract the signals of the three mounters. We used such band-limited signals as the input for the FHMM (Fig. 7a).

We also obtained ground-truth data $x_{\text{GT}}^{(k)}$ for each mounter for use in accuracy evaluation by applying the above preprocessing to respectively measured single-machine current waveforms I_1, I_2, and I_3. We set the number of factors to $K = 3$ and the number of process states of each factor for a designed process duration of T=400 (40 sec) for each mounter per PCB.

B. Results

Figs. 7b and 7c show the disaggregated signals as estimated with the proposed method, as well as with an ordinary unconstrained FHMM with the number of states being $M = 5$.

	Proposed Method	Unconstrained FHMM			
# States per factors M	401	2	5	10	30
# Non-zero elements in transition matrices	402	4	25	100	900
Average error in disaggregation	0.91	1.24	1.25	1.30	1.34

Table 1: Errors in disaggregation E_{disaggr} during 192-minute measurement in which the line was producing a type of product. The errors are averaged over 5 initial parameters.

With the proposed method, the disaggregated signal of each factor showed specific cyclic patterns. This reflects the fact that the mounters perform different processes even if they are of the same type (i.e., they put different parts on PCBs in a different order). These patterns are obtained by the deterministic one-way structure of the model, enabling successful disaggregation. By way of contrast, disaggregation failed with an unconstrained FHMM and almost all input features were reproduced by a single factor, #1, implying that, without constraints, it is hard to learn signal patterns specific for the mechanical workings of the mounters.

The accuracy of disaggregation was evaluated on the basis of the RMS error between disaggregated signals and ground-truth data for each factor:

$$E_{\text{disaggr}} = \sqrt{\frac{1}{KN}\sum_{k=1}^{K}\sum_{n=1}^{N}\left\{x_{\text{GT},n}^{(k)} - x_{\text{est},n}^{(k)}\right\}^2}. \tag{6}$$

Since there was arbitrariness in the permutation of the factors (i.e., the selection of indices k for $x_{\text{est},n}^{(k)}$), we choose an appropriate one by minimizing E_{disaggr}.

As shown in Table 1, the proposed method resulted in less disaggregation error than did a conventional unconstrained FHMM. We can also see that the error with the unconstrained FHMM was minimal in the case of binary states ($M = 2$) and increased as the number of states increased. This implies that the greater the complexity of the transition matrix (i.e., the greater the number of states), the more difficult the learning of proper structures becomes, because of an excessive degree of freedom.

The proposed method also has an advantage in its interpretability. Since each cyclic pattern seen in Fig. 7b corresponds to the mounting process for an individual PCB, we can extract the conditions in the manufacturing system. This is shown in Fig. 8, in which each slanting line corresponds to a PCB flowing through mounters, and each point corresponds to a timestamp showing when a mounter has completed a process (i.e., the state has reached $s_{k,n} = \mathrm{p}_T$). The results of our estimations (Fig. 8a) agree well with actual data obtained from machine logs (Fig. 8b). From Fig. 8, we can also obtain further information valuable for improving productivity. For example, the number of lines crossing a vertical axis at any specific time indicates the number of PCBs remaining in buffers and mounters. The gap at around 10:15 indicates the situation of vacant buffers, in which the first mounter has failed and all the others are

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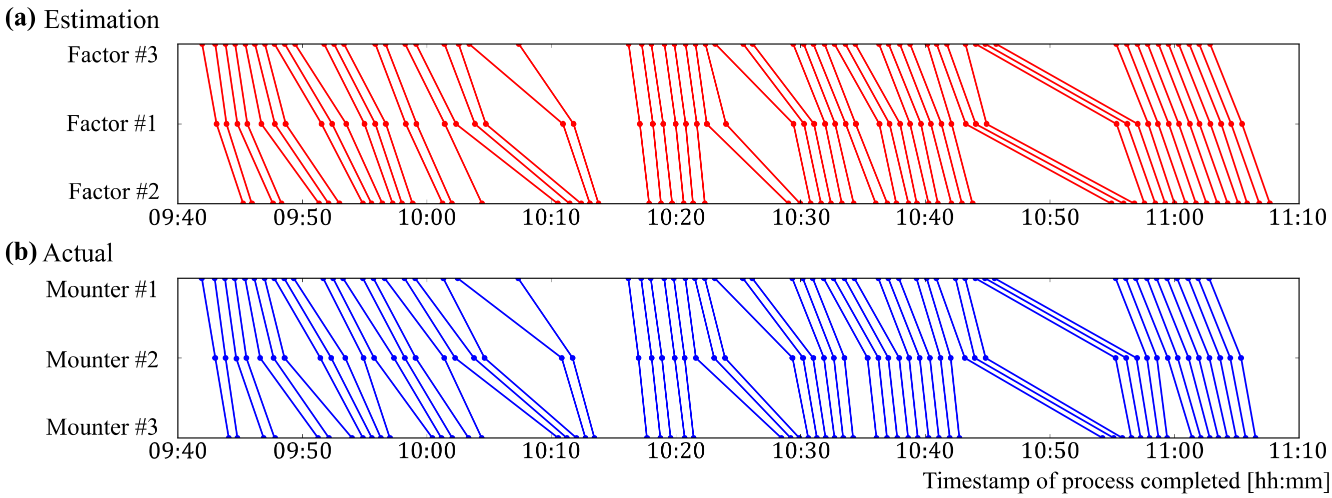

Fig. 8: The flow of PCBs through three mounters. (a) Estimated by FHMM with machine behavioral model, in which factors were ordered so that no PCBs would flow adversely. (b) Actual data obtained from machine logs.

starving. In contrast to this, all buffers and mounters are filled at around 10:50, implying that the system is blocked owing to a failure in the last mounter. Such information is useful to factory managers for creating manufacturing plans and for designing new systems to reduce curtailable loss, such as will occur with blocking or starving.

VI. SUMMARY

In this paper, a non-intrusive monitoring method has been proposed for monitoring conditions in manufacturing systems by means of only a single current sensor placed on a power supply line. For accurate disaggregation of current signals, we have proposed an FHMM-based model combined with behavioral models of manufacturing-machines. Application of the proposed method to an actual system results in fewer errors in disaggregation as compared with the application of conventional methods. Further, the model's interpretability offers information valuable for productivity, such as the reasons for and timing of manufacturing-process stoppages.

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