# The research of hidden Markov models for overall equipment effectiveness analysis in smart manufacturing system

*Chia*-Yu Hung[*] and *Chen*-Yang Cheng

Industrial Engineering of Management, National Taipei University of Technology, Taipei, Taiwan

**Abstract.** In the manufacturing industry, excellent product quality and increased production flexibility can be achieved by eliminating waste and improving production efficiency. In the past, the manufacturing industry used manual records of production information, but this method is characterized by low efficiency and high error rates. Even if a programmable logic controller and radio-frequency identification are employed, problems still occur because of constraints such as different machine types and high costs. The use of a cyber–physical system and information visualization requires the collection of manufacturing information in order to facilitate the analysis of manufacturing data. Monitoring the machining status. This study proposes an approach for segmenting machine-processed signals. With plug-and-play noninvasive current-sensing equipment to collect machine production information, this approach can immediately determine the state of the manufacturing process and calculate the machine utilization, machine production cycle, and production quantity. The goal is to enable the use of this method with this equipment, improve machine utilization, instantly identify the production quantity, and reduce equipment idle time to reduce manufacturing waste, thus rendering production management more convenient and faster.

## 1 Introduction

The market demand for customized products, which requires high-quality, low-cost products and fast delivery, the manufacturing industry must ensure that the operating time of machines exhibits more flexibility, adaptability, and intelligent decision-making. Features of Industry 4.0 must be adapted in the manufacturing industry, one of which is cyber–physical systems (CPSs). A CPS combines the network information world with the real world of physics. Therefore, a CPS must collect information to effectively integrate an actual situation, and then through information visualization (infovis), it can transform abstract data into an intuitive presentation. Infovis can transform the data into valuable information. Using infovis in factory management indicators and applying it in plant management can help the plant to effectively analyze manufacturing problems. This will increase flexibility and adaptability and thus facilitate achieving high-quality, low-cost products and fast delivery. In factory management, overall equipment efficiency (OEE) is the most commonly used indicator to measure the operation of production equipment. It simplifies complex problems in manufacturing and reformulates them through simple indicators. Using OEE to measure equipment operation is the most effective method of analyzing the efficiency of a manufacturing system. In this approach, the overall efficiency of a factory is analyzed in terms of equipment availability, performance, and quality.

The manufacturing process usually involves monitoring the state of a machine and the progress of production to improve efficiency. In the past, this information was obtained orally or was manually copied onto paper, and these methods are inefficient and have a high error rate. With technological progress, the demand for automatic production monitoring systems, such as the widely used programmable logic controllers (PLCs). However, a PLC is limited to different types of machines and different operating systems. The processing of information in a production line requires a considerable amount of money and time. Consequently, many plant managers use radio-frequency identification (RFID). However, this method is excessively expensive, because it requires the use of a large number of tags. In addition, the message between the tag and the reader can be easily truncated and has a limited usage range and distance.

In general, factories use an electricity consumption-based monitoring approach, because production equipment typically accounts for the majority of electricity consumption in factories. In this approach, current-sensing devices are used to noninvasively monitor production equipment on the basis of current signals; hence, this approach is not limited by the aforementioned constraints.

This paper presents an approach for analyzing machine status signals, and it can obtain machine production information using noninvasive current-sensing devices. This approach can distinguish between the signals produced during processing and can yield information on different statuses, in addition to calculating equipment

---

[*] Corresponding author: claire830110@gmail.com

availability, processing period, and production quantity. The objective of the proposed approach is to achieve a "plug-and-play" function, improve machine utilization, identify production quantity immediately, reduce equipment idle time, and manage production progress instantly, thus reducing resource wastage in the manufacturing process. This approach increases the speed and convenience of production management.

## 2 Related work

OEE is a simple and practical production management tool used in the manufacturing industry to measure actual and theoretical production capacity levels by analyzing equipment availability, performance, and quality. OEE facilitates identifying the cause of equipment-related problems. Ljungberg [1] stated that in total productive maintenance (TPM), the severity of the loss of different pieces of production equipment must be assessed to optimize resource allocation. In the manufacturing industry, collecting production site data is essential for the real-time monitoring of production conditions. With technological progress, the demand for automatic production monitoring systems, such as the widely used PLCs, has increased. Lin, Lin [2] developed a PLC system for automatically monitoring the quality of eggshells; this system can identify abnormal eggs with a success rate of >80%. In addition to PLCs, some manufacturing systems employ RFID. A tag is attached to each product, and an RFID reader is subsequently used to receive the tag information; thus, information on the product can be obtained immediately to collect production data. Wang, Cao [3] used RFID to obtain accurate production data for monitoring manufacturing systems and to obtain data from RFID tags and readers in order to analyze production information.

Signals can be analyzed through various methods; the most common methods are described herein. A wavelet transform is a commonly practiced time–frequency analysis method. This approach entails using a series of fundamental wavelet transforms to simultaneously analyze the time domain of the original signal, as well as the frequency domain [4]. The fundamental wave of the wavelet transform exhibits the characteristics of elastic time and frequency; this wave widens at low frequencies and yields time-domain information. Conversely, the fundamental wave narrows at high frequencies and yields frequency-domain information. Gritli, Zarri [5] used a wavelet transform-based diagnostic method to detect faults in three-phase wound rotor motors. Through the FT, the signal is decomposed into several sine wave frequencies. In other words, the FT is the sum of many sine functions. Therefore, the FT is often used for spectral analysis [6]. Peng, Chu [7] applied the fast FT (FFT) and wavelet transform to vibration signals and reported that the time–frequency characteristic of the vibration signals can be used to obtain fault characteristics.

Fault signals contain noise and other interference, rendering the fault characteristics difficult to identify.

Therefore, effective noise filtering is crucial in diagnosing machine problems. Mechanical failure-related signals are usually nonlinear, and the information is nonstationary. Huang, Shen [8] proposed a novel adaptive signal analysis method called empirical mode decomposition (EMD), which decomposes complex vibration signals into several inherent modal functions (IMFs). Each IMF represents a single shock signal component. After decomposition, each IMF has only one frequency at any given moment; therefore, the time–frequency distribution of the complex signals can be clearly defined and presented. A different instantaneous frequency calculation method is used to obtain each IMF instantaneous frequency and instantaneous amplitude to construct the time–frequency energy distribution. The resulting spectrum is known as the Hilbert time spectrum. This spectrum is integrated with time to obtain the frequency–energy relationship plot, called the marginal Hilbert spectrum. In the marginal Hilbert spectrum, different IMFs represent different signal characteristics, and faults can be identified by analyzing the different signal characteristics. Musaruddin and Zivanovic [9] proposed an EMD method for decomposing faulty power signals and distinguishing between the power failure signals of different sections by observing the anomalous segments on the Hilbert time–frequency diagram. DTW is one of the methods utilized for exploring time series data. It is a dynamic programming method and can determine the similarity between two groups of the same length or different length time series. DTW is applied to time series to measure similarity. Muda, Begam [10] analyzed voice messages by using the mel frequency cepstral coefficient (MFCC). The analysis results were uploaded to a database, and DTW was applied to match voice signals from an external environment with the voice signals in the database. Anguera, Macrae [11] proposed an unbounded DTW (U-DTW) method, which improved the shortcomings of DTW. The rule of the U-DTW method is to determine the possible match between two sequences by using a fixed range for forward and backward calculations and using the minimum length $L_{min}$. Thus, calculating unnecessary similarities can be avoided, consequently reducing the calculation time. U-DTW can commence from any point of comparison, and the average of each step is used to meet the conditions to determine the path; therefore, calculating all the values is not required. Miro and Macrae [12] applied U-DTW to speech matching and compared it with other DTW methods. The results revealed that U-DTW is fast and accurate. HMMs are used to determine hidden and unknown parameters from parameters that can be observed. HMMs can be applied in various situations. Mon and Tun [13] used the MFCC to decompose the speech signals of different words, and they subsequently entered these signals into different HMMs. The results revealed that the higher the number of HMMs, the higher the accuracy of the model.

## 3 Research Method

Figure 1 presents a flowchart of the proposed approach. In this approach, the signal is preprocessed to facilitate its analysis. Next, the signal is divided into numerous segments. These cut signals are analyzed to determine their status. The status of each signal segment can be determined by the characteristics of each signal segment. The availability of the machine can be calculated by determining the processing section and nonprocessing section of the time. Next, every state is trained separately, and then the model is established and subsequently compared with the signal status. Finally, the processing status of the signal is analyzed, and the production quantity is calculated.
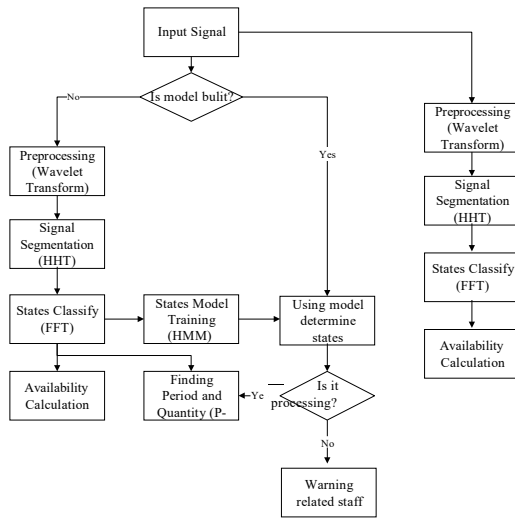


**Fig. 1.** Flowchart of research method

## 4 Experimental results

We propose a method for ascertaining current processing status, production cycle time, production quantities, and equipment availability through signal analysis and using noninvasive current-sensing hardware based on current signals to connect to equipment to collect current signal information. In the proposed approach, the signal is first segmented and classified, and the segmentation and classification results are then used to calculate equipment availability and the production cycle time and quantity. Finally, an updated classification model is established to ensure the same processing states can be quickly resolved and analyzed. Figure 2 provides the experimental data used in this study. The experimental scenario included equipment standby, refueling, processing product A, breakdowns, stoppages, and processing product B. Six different states were considered. The experiment results show in table 1~3 and figure 3.
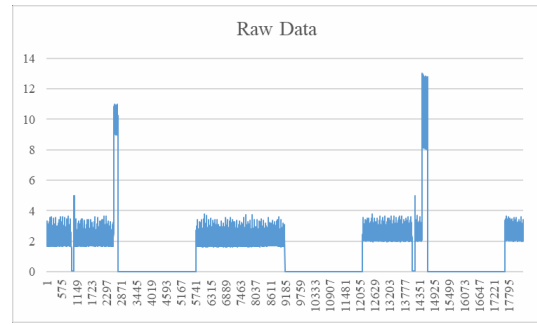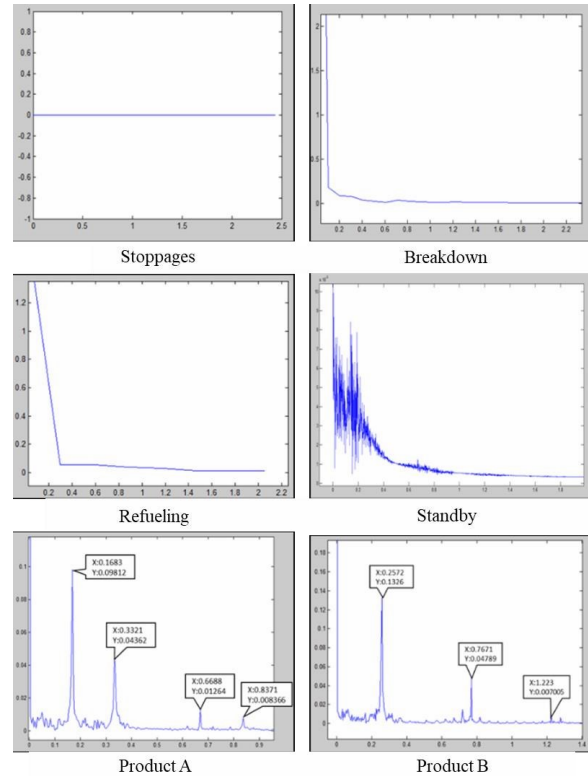


**Fig. 2.** Experimental data



**Fig. 3.** FFT comparison in different states

**Table 1. HHT segment error rate.**

|  | Standby | Refueling | Breakdown | Stoppages | Product A | Product B |
|---|---|---|---|---|---|---|
| HHT data length | 4969 | 144 | 218 | 2999 | 10905 | 4420 |
| Actual data length | 5538 | 149 | 219 | 2930 | 10384 | 4435 |
| error | 569 | 5 | 1 | 69 | 521 | 15 |
| Error rate | 10.3% | 3.4% | 0.5% | 2.4% | 5.0% | 0.3% |

**Table 2. Actual availability and calculated availability**

| Actual availability | Calculated availability | Error |
|---|---|---|
| 71.5% | 74.2% | 2.7% |

**Table 3. Results of processing cycle time and quantity**

|  | Cycle time (sec) | Actual quantity | Calculated quantity | Error | Error rate(%) |
|---|---|---|---|---|---|
| Product A | 5.8 | 345 | 348 | 3 | 0.87% |
| Product B | 4 | 226 | 222 | 4 | 1.77% |

## 5 Conclusion

In recent years, the concept of Industry 4.0 has been widely applied in the manufacturing industry. Typically, PLCs and RFID processes are implemented to collect processing information and monitor the production site in real time. Therefore, this paper presents an approach for analyzing machine status signals, and this approach can be used to obtain machine production information by using noninvasive current-sensing devices. The proposed algorithm involves four stages: noise elimination, signal cutting and segmentation, signal state classification, machine availability calculation, and production quantity calculation. Finally, to enable managers to quickly ascertain the processing state, the classified states are trained to construct a model.

To prove the accuracy and validity of the proposed state segmentation method, an experiment was conducted on six states: standby, refueling, failure, shutdown, product A, and product B. The purpose of this study was to identify the various states in the manufacturing process and to calculate equipment availability and the production quantity. After data analysis, the average error associated the determination of states in this study was less than 4%, the error associated with the determination of equipment availability was less than 3%, and the error associated with the determination of production quantity was less than 2%. Therefore, the proposed method is highly accurate in determining the status, availability, and production quantity. Applying this method to manage machine status and availability can assist managers to master the state of real-time processing and reduce machine idle time.In the proposed approach, the real-time calculation of the quantity of production can reduce the number of human errors caused by missing data. Moreover, the approach can enable managers to gain immediate knowledge of the progress of production and improve machine scheduling. Finally, training the classified states to construct a model expedites the determination of production states. Therefore, the proposed approach can be applied to factories.

## References

1. Ljungberg, Õ ., Measurement of overall equipment effectiveness as a basis for TPM activities. International Journal of Operations & Production Management, 1998. 18(5): p. 495-507.

2. Lin, J., et al. An automatic system for eggshell quality monitoring. in 2001 ASAE Annual Meeting. 1998. American Society of Agricultural and Biological Engineers.

3. Wang, B., et al., Fundamental technology for RFID-based supervisory control of shop floor production system. The International Journal of Advanced Manufacturing Technology, 2011. 57(9): p. 1123-1141.

4. Mallat, S., A wavelet tour of signal processing. 1999: Academic press.

5. Gritli, Y., et al., Advanced diagnosis of electrical faults in wound-rotor induction machines. IEEE Transactions on Industrial Electronics, 2013. 60(9): p. 4012-4024.

6. Sedláček, M. and M. Titěra, Interpolations in frequency and time domains used in FFT spectrum analysis. Measurement, 1998. 23(3): p. 185-193.

7. Peng, Z., F. Chu, and Y. He, Vibration signal analysis and feature extraction based on reassigned wavelet scalogram. Journal of Sound and Vibration, 2002. 253(5): p. 1087-1100.

8. Huang, N.E., et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. in Proceedings of the Royal Society of London A: mathematical, physical and engineering sciences. 1998. The Royal Society.

9. Musaruddin, M. and R. Zivanovic. Signal segmentation of fault records based on Empirical Mode Decomposition. in TENCON 2011-2011 IEEE Region 10 Conference. 2011. IEEE.

10. Muda, L., M. Begam, and I. Elamvazuthi, Voice recognition algorithms using mel frequency cepstral coefficient (MFCC) and dynamic time warping (DTW) techniques. arXiv preprint arXiv:1003.4083, 2010.

11. Anguera, X., R. Macrae, and N. Oliver. Partial sequence matching using an unbounded dynamic time warping algorithm. in Acoustics Speech and Signal Processing (ICASSP), 2010 IEEE International Conference on. 2010. IEEE.

12. Miro, X.A. and R. Macrae, Fast partial pattern matching system and method. 2014, Google Patents.

13. Mon, S.M. and H.M. Tun, Speech-To-Text Conversion (STT) System Using Hidden Markov Model (HMM). International Journal of Scientific & Technology Research, 2015. 4(6): p. 349-352.