Data-Driven Approach of Fault Detection for Customized Manufacturing

Allen Chang and Yaw-Jen Chang*

Abstract—**This paper presents a systematic approach of fault detection for the customized manufacturing. The proposed approach involves offline calculation and online implementation. The discrete sampled signals are first collected from machine for offline calculation. Based on the control system theory, the settling time and the control limits of the system dynamic behavior can be estimated without realizing the exact model of the machine. These calculated values are used as the thresholds for online implementation. In our simulations, malfunctions occurring in the transient state and in the steady state can be correctly detected. For customized manufacturing, this approach can monitor the manufacturing under different process settings.**

Index Terms—**Fault detection, customized manufacturing, transient state, steady state**

I. Introduction

THE improvement of technology, transportation, and computer nowadays connects culture and economic from different countries into an intertwined and interdependent network. Globalization enhances the competitiveness of industry environment, leading to a transformation toward manufacturing customization. Unlike past years, firms today shift their focus from increasing productivity to optimization and innovation.

The concept of "the fourth industrial revolution (Industry 4.0)" launched out by Germany leads the world in such a transformation. Industry 4.0 emphasizes the use of cyber-physical system and Internet of Things to ultimately build a self-intelligent and self-learning "Smart Factory" [1–3]. Cyber-physical system combines scientific computation with sensor networks and actuators to create a network of computational elements interacting with the physical world. By collecting and analyzing information from physical entities, machines are capable of predicting their own degradation and making the optimal decision, turning themselves into self-aware and self-maintained. In addition, the Internet of Things embeds machines with computer systems, especially the Internet, and allows machines continuing to collect and exchange data. By doing so, the Internet of Things improves machines' performance and efficiency. Altogether, cyber-physical system combining with the Internet of Things becomes a large and complex network known as the "Smart Factory".

As mentioned earlier, manufacturing customization will enhance firms' competencies. However, the variety of products and the complexity of manufacture will also make the manufacturing process of customization hard to manage. Furthermore, any equipment faults or malfunctions will degrade machine's health and performance and lead to defect products or scraps so that the manufacturing cost increases. Under such a highly complex manufacturing environment, manufacturing processes usually suffer from a high level of nonlinearity and a wide range of variation on process parameters.

For process monitoring and fault detection, there are several kinds of techniques available but, however, lots of methods only work under limited conditions. In the real world, similar machines may be required to perform different tasks under different environment. As a result, incorrect method may cause false prediction and wrong diagnosis, leading to an incorrect outcome.

It is not surprising that the model-based method is popularly used in the industry. It utilizes an explicit mathematical model of the monitored system. Once the model is precisely built-up, any system fault would be difficult to flee from the detector. However, the performance of the model-based approach depends strongly on the accuracy of the models.

Currently, model-free methods, or called data-driven approaches, are widely used in practice, for example, statistical process control (SPC) is one of the most commonly seen methods for machines maintenance and manufacturing process monitoring, by controlling and improving a process through statistical analysis [4]. Engineers will measure the mean and variance from collected data and compare them with the control chart to detect data outliers and thus make the optimal decision. However, the main issue of statistical process control is that it is based on the assumption that the data must be identically, independently and normal distributed. As a result, SPC does not work properly on most of the waveform signals.

Obviously, correct machine maintenance and fault detection are challenging and hard to achieve. Creating an effective and proper fault detection technique is yet required further research. With these issues presented above, this paper is dedicated to develop a simple computation method for machine monitoring and fault detection, especially for the case of manufacturing customization in Industry 4.0.

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II. METHOD AND PROCEDURE

A fault is an abnormal change in the characteristics of a machine leading to undesirable performance and products. This paper proposes a methodology that can be used to detect machine's problems in manufacturing process and avoid false alarm. We herein use the temperature control as an example. Usually, the time response of a process can be divided into two parts: the transient response and the steady-state response. When the machine is first turned on, it will undergo a process of heating up before getting to the ideal and steady temperature for works. During that period of time when machine is heating up, the status of machine is known as being in the transient state. In transient state, machine's temperature is relatively inconsistent comparing to the steady-state temperature. Generally speaking, monitoring the steady state is quite easier than the transient state. For the steady state, it is fair to say that the machine is functioning incorrectly if the temperature changes dramatically. This rule, however, cannot apply for machine in the transient state since machine's temperature is continuously increasing in that time span. As a result, different methodologies are required for fault detection of the machine in both the transient and the steady states and it is important to monitor the entire machine dynamics.

To implement process monitoring and fault detection, the data of machine's temperature at certain period of time must be collected first. This proposed method checks the transient state and the steady state, respectively, without realizing the exact model of the machine. The procedure, as shown in Fig. 1, contains two steps: offline calculation and online implementation. The step of offline calculation is to estimate some critical parameters that will be used in the online implementation for process monitoring.

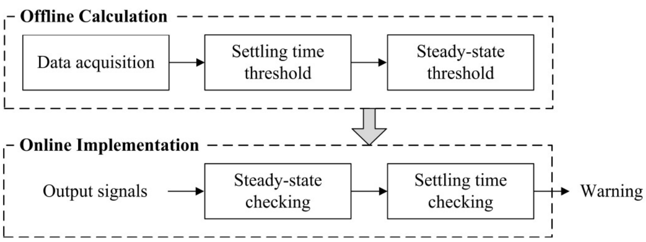

Fig. 1. Procedure for process monitoring.

In this study, we consider the second-order control systems whose analysis generally helps to form a basis for the understanding of analysis of higher-order systems. The block diagram is shown schematically in Fig. 2. The closed-loop transfer function of a second-order system with unity feedback can be written as

$$\frac{Y(s)}{R(s)} = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2}$$

where ζ and ω_n are real constants, called damping ratio and undamped natural frequency, respectively. Obviously, the dynamic behavior of the second-order system is related to the parameters ζ and ω_n. If $0 < \zeta < 1$, the system has oscillatory transient response. It becomes more difficult to draw out the signal characteristics. Nevertheless, the transient response is necessarily important, since both the amplitude and the time duration of the transient response must be kept within tolerable limits.

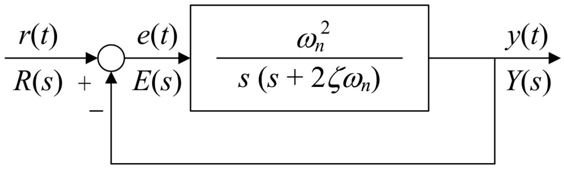

Fig. 2. Second-order control systems.

The step-function input to the second-order control system is considered. It represents an instantaneous change in the input. For example, if we activate an electric heater through the operation of a switch, a step-function constant voltage is applied to the heater. Thus, for the example of the temperature control, an engineer must provide the settings of desired temperature and heating duration to the control system. It is desirable that the transient response of heating process be sufficiently fast. Otherwise, the substrate to be heated might not gain enough thermal energy. A critical parameter in the transient response is then the settling time which is defined as the time required for the response to reach and stay within a range of 5% of the desired temperature. Furthermore, the range of 5% of the desired temperature is also adopted as the control limit to monitor the steady-state response.

Moreover, the time output signals of control systems normally are not analytical signals. That is, the mathematical expressions of these signals are difficult to be derived. In practice, the output signals are usually acquired by sensors, resulting in the discrete sampled-data. Hence, the discrete sampled-data of temperature are collected from the machine in the offline calculation stage. The logical settling time must be calculated using the sampled-data as the threshold for the online implementation.

A. Estimating the threshold of settling time

Using the sampled-data collected in the offline calculation stage, one can realize the time at which the output response reaches the 5% range of the desired temperature. However, it is not suitable to be used as the threshold value because different products might require different temperature settings. Moreover, the machine performance might degrade after long term operation. Therefore, a flexible threshold value should be considered.

Based on the theory of control systems [5,6], the damping ratio must be between 0.4 and 0.8 for a desirable transient response of a second-order system. Thus, a reasonable settling time for different temperature settings can be estimated as:

$$t_s = \frac{3}{\zeta\omega_n} \text{ (5\% criterion)}$$

where t_s is the settling time and ζ is equal to 0.4. Unfortunately, the undamped natural frequency ω_n is unknown.

To estimate ω_n, another specification defined in the control system theory can be utilized. The rise time t_r is the time required for the response to rise from 10% to 90% of its final value. For the second-order system, the rise time can be approximated as:

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$$t_r = \frac{31 - 0.4167\zeta + 2.917\zeta^2}{\omega_n}, \quad 0 < \zeta < 1.$$

From the collected sampled-data, we estimate the rise time to be the time at which the sample:

(sample(i) > 80% * final value) AND
(sample(i) < 0.9 * final value)

or

90% * Δt/sample(1)

where Δt is the sampling time of the sensor. Thus, the undamped natural frequency ω_n can be estimated. Finally, the settling time can be estimated for the damping ratio being 0.4 and 0.8, respectively, and the maximum value is chosen as the threshold.

B. Estimating the steady-state control limits

The damping ratio dominates the dynamic behavior of the transient response. The transient response is oscillatory if $0 < \zeta < 1$. Therefore, we cannot determine whether the response is in the steady state or not if:

(sample(i) > 0.95 * final value) AND
(sample(i) < 1.05 * final value).

If the response reaches the stays within a range of 5% of the final value, the maximal oscillatory change must also satisfy:

$$\frac{\text{sample}(i) - \text{sample}(i-1)}{\Delta t} < \frac{0.1 \times \text{final value}}{\Delta t}$$

Fig. 3 shows the concept.

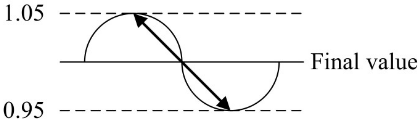

Fig. 3. Steady-state control limits

III. Simulations and Results

Once the threshold values for the transient state and the steady state are determined, they can be used for online implementation. In our simulation, we assume that the temperature control system is:

$$\frac{Y(s)}{R(s)} = \frac{25}{s^2 + 4s + 25}$$

Actually, this mathematical model is unknown to us. We estimate the aforementioned threshold values using only the discrete sampled-data. Assume that the sampling time of the sensor is 0.5 sec. The input is the unit-step function.

After the calculation, the threshold of the settling time is 2.317 sec. Now, four cases are considered. Figures 4 – 7 shows the results. In these figures, the solid line is the ideal response of the temperature control system, while the asterisks denote the actual sampled response data.

Case 1:

If the temperature control system is subjected to a disturbance, leading to have a larger oscillatory transient response. Then, the output has a larger maximum overshoot. It takes more time to reach the steady state. As shown in Fig. 4, our method correctly detects the problem by comparing the settling time. Although the maximum overshoot is an important specification in the transient response, we do not need to calculate and monitor this value.

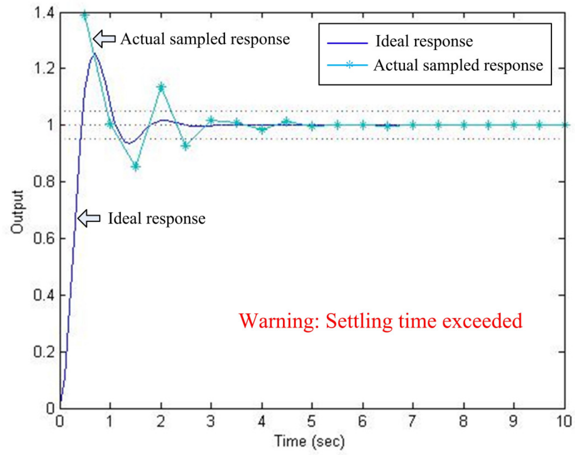

Fig. 4. Case of larger oscillatory transient response.

Case 2:

If the temperature control system is subjected to a malfunction so that the temperature cannot be raised as soon as possible. The transient response exhibits no oscillation. Similarly, it takes more time to reach the steady state. Our method correctly detects the problem through the comparison of the settling time, as shown in Fig. 5. If the system has a serious malfunction, a longer settling time is needed. Obviously, this kind of cases can be monitored by our method.

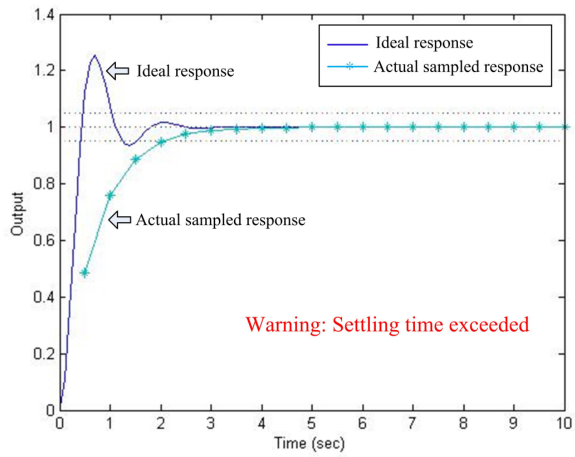

Fig. 5. Case of slow temperature raising.

Case 3:

If the temperature control system is subjected to a malfunction that occurs when the temperature has reached its steady state. The system is correctly heating up and the transient response exhibits normal oscillation. However, the temperature cannot keep steady. It is a worse case because the heated substrates do not have identical thermal energy piece-to-piece.

For this case, the sampled response data are compared with

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the control limits of steady state. The malfunction can be monitored by our method, as shown in Fig. 6.

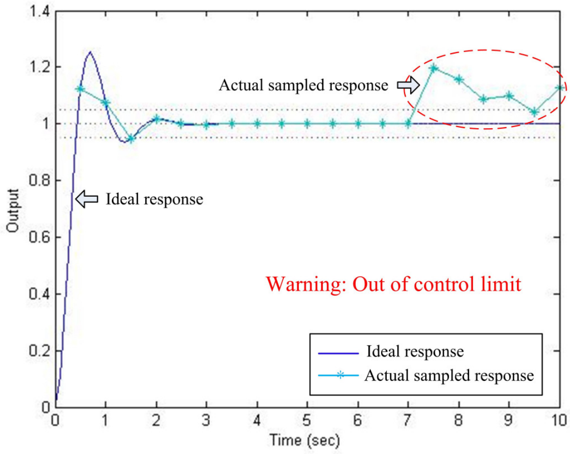

Fig. 6. Case of malfunction in the steady state.

Case 4:

For the customized manufacturing, the process might require different temperature settings and inconsistent heating durations. Once the malfunction occurs, the sequent machining process might be stringently affected. In this simulation, we assume that the temperature control system is subjected to a malfunction occurring at the steady state of the second manufacturing process. Furthermore, the temperature cannot be raised fast at the transient state of the third manufacturing process. It is a combined circumstance of the aforementioned cases and the malfunctions can be monitored by our method, as shown in Fig. 7.

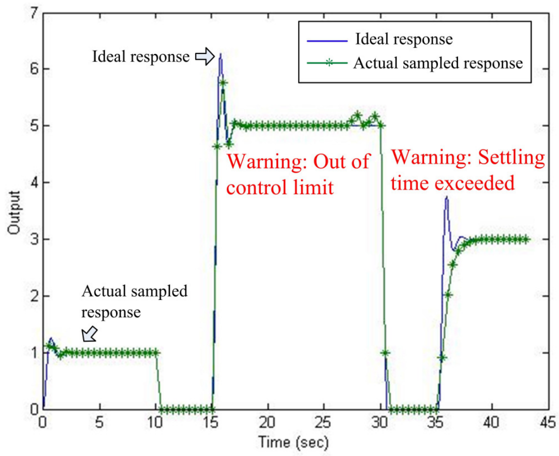

Fig. 7. Process monitoring for customized manufacturing.

IV. Conclusion

Industry 4.0 emphasizes the use of cyber-physical system and Internet of Things to ultimately build a self-intelligent and self-learning "Smart Factory" for the customized manufacturing. This proposed fault detection method is a data-driven approach. Based on the control system theory, the settling time and the control limits of the system dynamic behavior can be estimated without realizing the exact model of the machine. The method can detect the malfunctions effectively in the transient state and in the steady state. It can be easily involved into the system of Smart Factory.

References

[1] D. Gorecky, M. Schmitt, M. Loskyll, and D. Zühlke, "Human-Machine-Interaction in the Industry 4.0 Era," *Proc. of IEEE International Conference on Industrial Informatics* (INDIN), 2014, pp. 289–294.

[2] J. Lee, H.-An. Kao, and S. Yang, "Service Innovation and Smart Analytics for Industry 4.0 and Big Data," *Procedia CIRP*, vol. 16, 2014, pp. 3–8.

[3] A. Ditter, D. Fey, T. Schön, and S. Oeckl, "On the Way to Big Data Applications in Industrial Computed Tomography," *Proc. IEEE International Congress on Big Data*, 2014, pp. 792–793.

[4] C. J. Spanos, "Statistical Process Control in Semiconductor Manufacturing," *Proc. of IEEE*, vol. 80, 1992, pp. 819–830.

[5] K. Ogata, *Modern Control Engineering*, 2010, Pearson.

[6] F. Golnaraghi and B. Kuo, *Automatic Control Systems*, 2010, Wiley.

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