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Confidence estimation of feedback information for logic diagnosis

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ABSTRACT

This paper proposes an estimation method for the confidence level of feedback information (CLFI), namely the confidence level of reported information in computer integrated manufacturing (CIM) architecture for logic diagnosis. This confidence estimation provides a diagnosis module with precise reported information to quickly identify the origin of equipment failure. We studied the factors affecting CLFI, such as measurement system reliability, production context, position of sensors in the acquisition chains, type of products, reference metrology, preventive maintenance and corrective maintenance based on historical data and feedback information generated by production equipments. We introduced the new 'CLFI' concept based on the Dynamic Bayesian Network approach and Tree Augmented Naïve Bayes model. Our contribution includes an on-line confidence computation module for production equipment data, and an algorithm to compute CLFI. We suggest it to be applied to the semiconductor manufacturing industry.

1. Introduction

Nowadays, semiconductor manufacturing operates in an intense competitive environment. Companies working in this industry are striving to improve process quality while also improving production equipment effectiveness. In recent years, research has been focused on virtual metrology (Min-Hsiung et al., 2007; Ferreira et al., 2009), dynamic control plan (Bettayeb et al., 2011), maintenance and Fault Detection and Classification (FDC) (Hong et al., 2012). However, these remain challenging areas. Semiconductor manufacturing is a complex process, and a variety of equipment (as shown in Fig. 1), including production and metrology equipment, continues to demonstrate a natural drift. If this drift becomes larger than the threshold value, it might result in propagation of significant failures, immediately affecting the production process and leading to a large number of products in the manufacturing process being scrapped. Therefore, it is critical to precisely and quickly locate the causes of failures for repair and maintenance purposes. Diagnosis solutions are then proposed. In this field of research, a number of approaches have been proposed including Fanti and Seatzu (2008), Cabasino et al. (2010), Genc and Lafortune (2003, 2005), Ru and Hadjicostis (2009), Ruiz-Beltran et al. (2006) and Elodie et al. (2010).

However, these approaches do not allow for uncertainty of feedback information to be easily taken into account. A key part of our approach is on-line confidence (uncertainty) computation based on the historical data and feedback information generated by production equipment. Several studies have been proposed to address the uncertainty related to diagnosis. Hong et al. (2012) presented an FDC approach, using a neural network in plasma etching, followed by investigation of the uncertainty associated with fault diagnosis. The evidential reasoning method via the Dempster–Shafer (DS) theory was used in this approach. Chavez et al. (2011) consider confidence of measured information uncertainty in qualitative reasoning. Information uncertainty can be quantified via measurements of non-specificity and conflict. The fuzzy sets method is used to determine the qualitative level of confidence for both AR (Approximate Reasoning) and ER (Evidential Reasoning) inference mode vector results associated with each scenario based on the available information. However, the confidence value is limited to a finite set of elements, e.g. {Very High, High, Medium, Low, Very Low}, and this method has identified a scenario that is a series of actions and events. Thus, these are inconsistent with the context and our issue. Simon and Weber (2006) focuses on methods for model reliability uncertainty. This approach proposes a specific integration of the Dempster–Shafer (DS) theory in Bayesian Network (BN) tools in order to handle the epistemic uncertainty problem and use the advantages of Bayesian Network tool power to model system reliability (Cobb and Shenoy, 2003). Nevertheless, this approach handles only the epistemic uncertainty of the system state according to epistemic uncertainty of component state without considering other system factors such as production context, type of products, variations in production and product specification.

In this context, we propose developing an approach dedicated to an on-line diagnosis system (Deschamps and Zamai, 2007) to help human operators locate equipment at the origin of a failure and analyze the impacts of failures in Automated Manufacturing Systems. The extensive approach is mainly based on calculation of confidence of feedback information derived from production

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equipment. Particularly, we focus on integrating the Bayesian Network to calculate confidence of reported information. To illustrate this issue, we suggest an application for a semiconductor manufacturing system.

The remainder of the paper is organized as follows: in Section 2, the study context is presented to introduce the issue. Section 3 presents the 'CLFI' concept and the main impacting parameters. The Bayesian Network approach is then described, and its major points are discussed in Section 4, followed by Modeling Dynamic CLFI in Section 5. The algorithm and implementation of the CLFI computation model is described in Section 6, while Section 7 gives the conclusion and future prospects.

2. Context and problem

Semiconductor manufacturing is an Automated Manufacturing System (AMS), structured around CIM architecture (Jones and Saleh, 1989) with three main parts: controlled system, control system and product flow (Fig. 2). The controlled system is a set of elementary functional chains (FCs) (Deschamps and Zamai, 2007) where its operating parts are controlled by the control system based on the information collected from the controlled system. Consequently, the behavior of the control architecture is generic and is based on the principle of observability (Cambacau, 1991). It allows use of the remote procedure call (RPC) principle to launch the requests which are sent to the lowest level (customer request) i.e. level 1 within the control system.

In reality, an AMS consists of hardware, software, organizational and human elements (Zio, 2009). It is subjected to uncertainties due to its operating parts (failures of sensors, actuators, etc.) and customer requests (variations in production and product specifications). In order to guarantee reactivity of the AMS, the reactive loop in the control system and dynamic reconfiguration are proposed in papers Courvoisier (1990) and Henry et al. (2012). The reactive loop is characterized by collaboration of several supervision, monitoring and control (SM&C) functions such as detection, diagnosis, prognosis, decision, and automatic control (Zamai et al., 1998). Consequently, depending on the operating mode (normal or abnormal running), the purpose of the coordination level is to manage a set of FCs by using services offered by these FCs (Fig. 2). In case of propagated failure in the product, detected by metrology equipment, the coordination level has to locate the origin of failure in the production equipment used in the failure.

Fig. 3 illustrates a classical production system of a semiconductor with four production (M1, M2, M3, M4) and metrology equipment items. A final product in such a system often requires more than 700 processing steps (Byungwhan and May, 1995). Product quality is ensured by the inspections carried out in a large number of steps during the production process with the embedded metrology (inside M1, M2, M3, M4). Each control step returns a report on process execution status to the coordination control module. Nevertheless, this metrology equipment in manufacturing systems implies a lack of confidence in feedback information derived from production equipment, essentially due to location and quantity of sensors in production equipment.

In Fig. 4, we present the problem associated with the open loop that may introduce doubts (uncertainties) as to the success of the operated service, thus implying an increased risk of (Not OK) product parts not being observed. This will result in the default response (OK) by the control module. A failure detected by the metrology equipment guarantees that one or more process steps have failed. Hence, to locate the origin of failure within production equipment, a large number of approaches (Lafortune et al., 2001; Deschamps and Zamai, 2007; Fanti and Seatzu, 2008) have been proposed. Particularly, Deschamps and Zamai (2007)

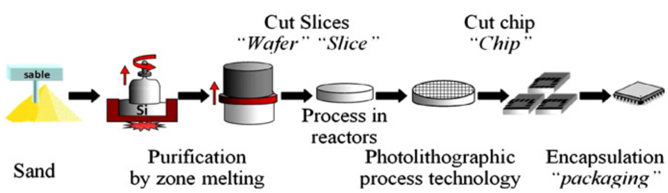

Fig. 1. Semiconductor manufacturing process.

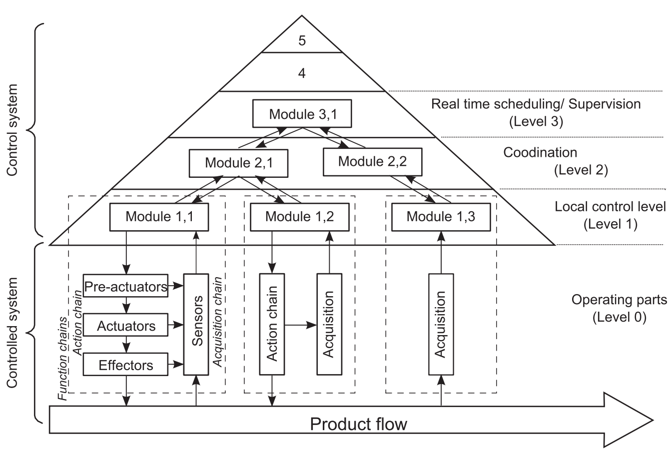

Fig. 2. Diagram on an AMS.

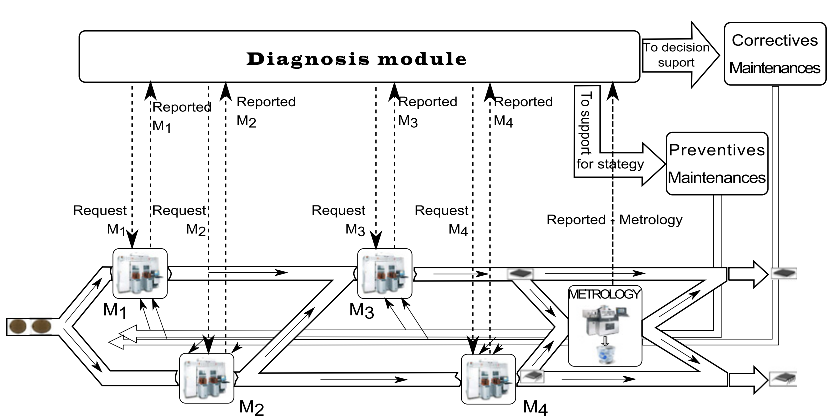

Fig. 3. Semiconductor production system.