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PREDICTIVE EQUIPMENT HEALTH BASED ON HIDDEN MARKOV MODEL AND PRODUCTION SCHEDULING

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ABSTRACT

Accurate monitoring of equipment health is one of the critical functions of intelligent manufacturing. Considering the equipment condition is interesting not only for maintenance but also for efficient production planning. Consequently, calculating the Remaining Useful Life (RUL) becomes an extension to support equipment prognostics. A two-phased Predictive Equipment Health with hidden Markov Models (PEHMM) is proposed in this research. The offline behavior learning phase brings together all historical manufacturing data into the HMM to study the dynamics of the equipment condition. Then, the online prognostic phase predicts short-/long-term indices given complete or partial information. By looking into the duration and transition between HMM states, the evolution of the equipment health can be traced, and the impact on the yield can be reduced accordingly. Furthermore, the PEHMM is expected to enhance the decision quality on the scheduling/dispatching of lots in production, the equipment utilization, and the monitoring of production yield.

Keywords: Equipment prognostics; Remaining useful life; Hidden Markov model

1 INTRODUCTION

In Total Productive Maintenance (TPM), conventional approaches to optimizing equipment effectiveness usually require defining the Overall Equipment Effectiveness (OEE) (Ahuja et al. 2008). The OEE is evaluated through three indices: Equipment availability, equipment performance, and product quality. The OEE has been widely accepted in modern industry standards as a quantitative tool for productivity assessment in manufacturing. However, the OEE is considered a lagging index given its computational nature based on historical data. To further improve the effectiveness of equipment by predicting product quality as well as process efficiency, the Predictive Overall Equipment Effectiveness (POEE) has been conceptualized (Kao et al. 2016). The POEE relies on Virtual Metrology (VM) to preview the real-time quality information for optimal process control. However, to make the predicted production quality accurate, real-time data, such as the equipment signals, are required. Therefore, predicting the equipment condition in the long run is still a challenging task, not to mention a predicted OEE that includes predictive product quality.

2 PREDICTIVE EQUIPMENT HEALTH WITH HIDDEN MARKOV MODEL

All the aforementioned lagging issues have motivated this research, where a Predictive Equipment Health with hidden Markov Models (PEHMM) is proposed to focus on the estimation of equipment health by utilizing the MES and optional FDC data rather than emphasizing virtual metrology. The PEHMM relies first on a Hidden Markov Model (HMM) to study the behavioral changes in the equipment. The offline behavior learning phase brings together all historical manufacturing data to build an HMM (Tobon-Mejia et al. 2012). In the online prognostic phase, the trained PEHMM takes the future production plan as the basic input to predict the equipment health in the long run.

As shown in Figure 1, the offline phase in the proposed PEHMM studies the behavioral models that illustrate different operating conditions of the equipment in the form of an HMM. Equipment features and process states are extracted based on the historical production data. The extracted features are then used to derive the parameters (π, A, B) required to construct the HMM via the Baum-Welch algorithm. The duration and transition probability between possible equipment states are calculated, and patterns that represent the equipment degradation dynamics are learned.

In the online equipment prognostic phase, given the production plan, e.g., MES data, detailed schedule, testing plan, and dispatching rules, the PEHMM exploits the learned models to identify the equipment current health state. If the optional real-time equipment sensor data are ready, the short-term equipment health can be computed. Otherwise, the equipment health, in the long run, is predicted without the real-time process data.

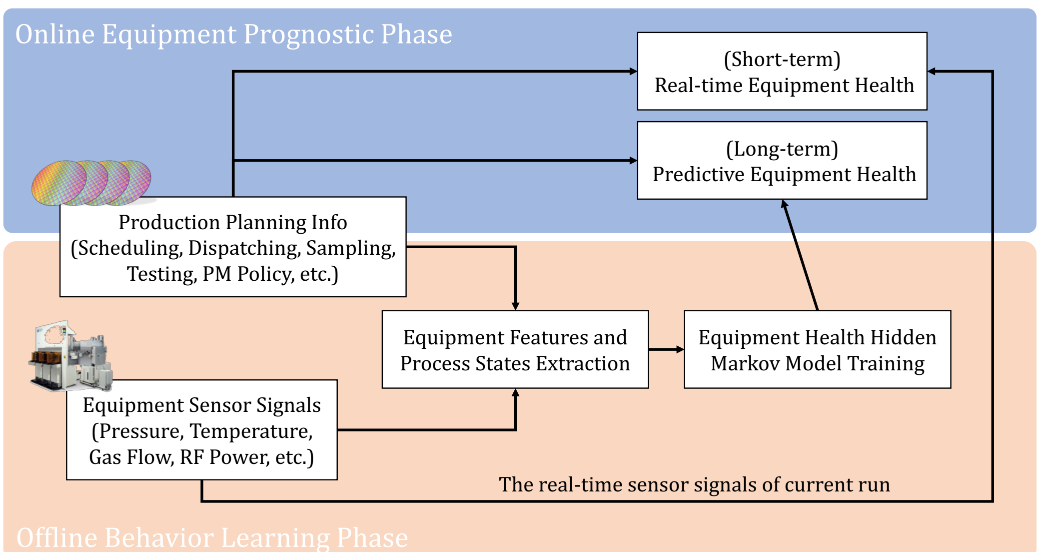

Figure 1: Proposed PEHMM framework.

3 ONGOING WORK

The conceptualization of the PEHMM is ongoing, and the potential datasets are under survey. A proof-of-concept example will first be performed to validate the feasibility of the PHEMM and to study potential issues. With the algorithms and model that will be refined, the PEHMM framework will be demonstrated on benchmark datasets at the conference.

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