

## Research Article

# Incoming Work-In-Progress Prediction in Semiconductor Fabrication Foundry Using Long Short-Term Memory

Tze Chiang Tin,<sup>1,2</sup> Kang Leng Chiew ,<sup>1</sup> Siew Chee Phang,<sup>2</sup> San Nah Sze,<sup>1</sup> and Pei San Tan<sup>2</sup>

<sup>1</sup>Faculty of Computer Science and Information Technology, Universiti Malaysia Sarawak, 94300 Kota Samarahan, Sarawak, Malaysia

<sup>2</sup>X-FAB Sarawak Sdn. Bhd., 1 Silicon Drive, Sama Jaya Free Industrial Zone, 93350 Kuching, Sarawak, Malaysia

Correspondence should be addressed to Kang Leng Chiew; klchiew@unimas.my

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Preventive maintenance activities require a tool to be offline for long hour in order to perform the prescribed maintenance activities. Although preventive maintenance is crucial to ensure operational reliability and efficiency of the tool, long hour of preventive maintenance activities increases the cycle time of the semiconductor fabrication foundry (Fab). Therefore, this activity is usually performed when the incoming Work-in-Progress to the equipment is forecasted to be low. The current statistical forecasting approach has low accuracy because it lacks the ability to capture the time-dependent behavior of the Work-in-Progress. In this paper, we present a forecasting model that utilizes machine learning method to forecast the incoming Work-In-Progress. Specifically, our proposed model uses LSTM to forecast multistep ahead incoming Work-in-Progress prediction to an equipment group. The proposed model's prediction results were compared with the results of the current statistical forecasting method of the Fab. The experimental results demonstrated that the proposed model performed better than the statistical forecasting method in both hit rate and Pearson's correlation coefficient,  $r$ .

## 1. Introduction

In semiconductor manufacturing, preventive maintenance (PM) is an activity that takes the entire tool offline to carry out prescribed maintenance activity in order to maintain or increase the operational efficiency and reliability of the tool and minimizes unanticipated failures due to faulty parts [1]. However, PM downtime can be costly because it takes significantly long hours. If there are insufficient back-up tools to process the incoming Work-in-Progress (IWIP) when the tool is taken offline for PM activities, a WIP bottleneck situation will be created which affects the linearity of the WIP distribution in the line.

Reducing cycle time is one of the main goals to ensure on-time-delivery to the customers, while ensuring that the wafers have good yields. Thus, it is necessary to do proper PM planning to minimize cycle time impact while ensuring the tool is operational reliable. To achieve this goal, PM should be done when the tool group has low IWIP. However,

the IWIP to a tool group has high variations as it is influenced by the conditions of the tools supplying the WIP to it, and various lots dispatching decision that changes dynamically every day.

In this paper, we present a multistep univariate IWIP prediction model to forecast the IWIP to a particular tool group in a semiconductor fabrication foundry (Fab) for the next seven days. We predict seven days ahead in this study as a requirement from the Fab. The problem domain is based on X-Fab Sarawak Sdn. Bhd., which has been abbreviated as the Fab. Long Short-Term Memory (LSTM) recurrent neural network is used in the prediction model to learn the historical incoming WIP pattern of the tool group to predict the future incoming WIP pattern of that tool group. LSTM has been used in various research areas such as traffic flow prediction [2], log-driven information technology system failure prediction to discover long-range structure in historical data [3], gesture recognition [4], voice conversion [5], and aircraft engines excess vibration events predictions [6].