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APPLIED PRODUCTIVITY AI/ML PLATFORM BASED LOT CYCLE TIME PREDICTION IN SEMICONDUCTOR MANUFACTURING

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ABSTRACT

Applied Productivity AI/ML platform is used to predict lot cycle time in semiconductor manufacturing fab. Artificial Intelligence(AI) and Machine Learning(ML) are disrupting Manufacturing Industry in several areas by augmenting engineers' efforts by providing predictions like lot cycle time and analytics like dynamic bottleneck. This platform support an end-to-end process at enterprise level scale for data engineers and ML/IE engineers to deliver a ML module/function in their production system. In this case study, General process flow of how to use this platform to deploy a ML function is introduced. Accurate prediction of cycle time (CT) plays an important role in the promises of a good delivery-time for semiconductor manufacturers. How to use this platform to build a ML model to predict lot cycle time and deploy this ML model into the production environment in semiconductor manufacturing fab is also explained. This case study shows the effectiveness and efficiency of this platform.

1 INTRODUCTION

Applied Productivity AI/ML platform is providing a flexible and powerful environment to cover all ML system development cycle[1]. Figure 1 depicts the basic architecture of the AI/ML platform.

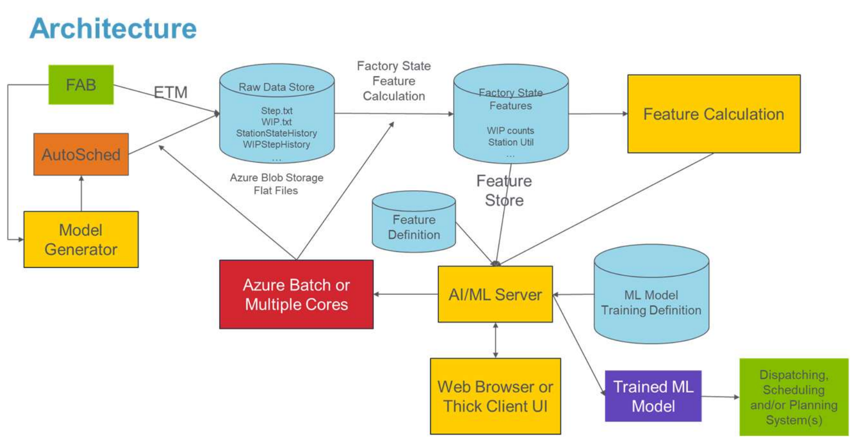

Figure 1: Applied Productivity AI/ML Platform Architecture

Each process in the machine learning lifecycle[2] (Data, Feature engineering, Training/Test and deployment/monitoring) are all covered and automated and programmable data and feature generation is provided. Furthermore Web UI based training/test and monitoring environment and APF Formatter based deployment is also available as key features.

2 ML MODEL BUILDING AND DEPLOYMENT

Data preparation, feature engineering, model training and testing and deployment/monitoring in the current production environment is the ML system development process. Using Applied Productivity AI/ML platform, this process will be easy and straightforward especially if a company is using Applied Productivity APF environment then this process will be automatic and programmable like Figure 2.
Fab-wide historical data and data augmentation[3], new data generated by AutoSched AP model are gathered and labeled automatically. Feature data is also extracted by programmable way based on pre-defined feature factors. ML model training, testing and final model exporting to a pickle file will be done using Solution UI. All of these process flow is managed by Activity manager job. Importing the ML model file (pickle files) into a Formatter rule by using python block is the final deployment step. Now it's ready to predict a lot cycle time for the remaining steps.

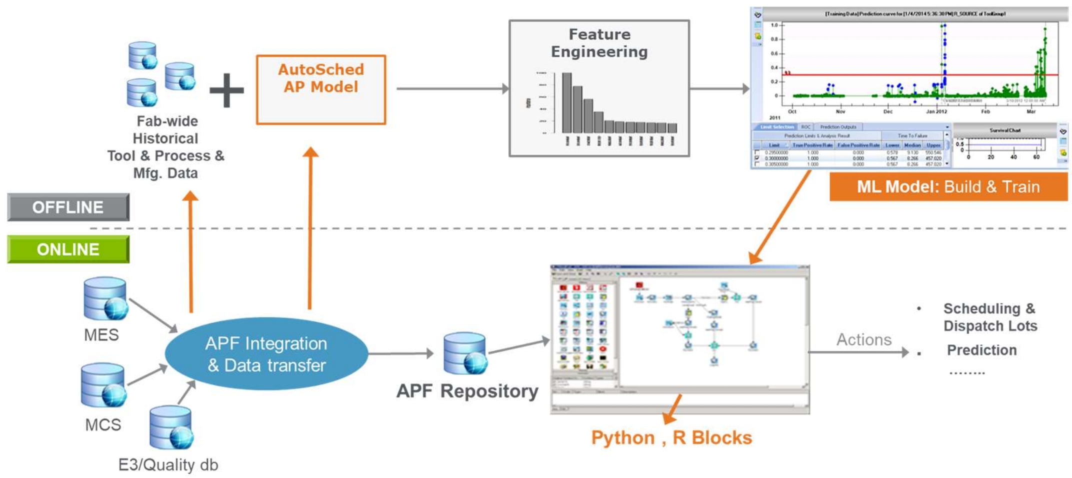

Figure 2: Applied AI/ML Platform : Algorithm Development and Integration Flow

3 ML MODEL BASED LOT CYCLE TIME PREDICTION

ML model for lot cycle time prediction is built and deployed by following the process explained above. Historical lot transaction data and various future simulation data could be used as the input data to train and test this model. Test and evaluation is done by basic metric like AUC, precision matrix and robustness test can be done by slice analysis. The result is the predicted lot cycle time by part, route and step pair(start, end). After deployment using Formatter(python block), model performance monitoring(accuracy, prediction or feature drift) can be done by APF Solution UI.

4 CONCLUSION

In this case study, Applied Productivity AI/ML platform is introduced and ML model based lot cycle time prediction case is explained as an use case of this platform. This kind of ML based use case could be easily built and deployed to the production by using Applied Productivity AI/ML platform. In the near future, This platform will be extended to build and deploy RL(Reinforcement Learning) based rule model in production by using simulation model based automatic data generation and labeling features.

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