ABSTRACT

Statistical KPI Forecast in Semiconductor Manufacturing

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Motivation

Semiconductor production is one of the most challenging and complex tasks in the environment of fabrication. Even in Europe, complexity of production processes is continuously increasing. At the same time, customer specific variations of products are transforming classical mass production operations into sensitive production networks with a wide range of different production classes. A typical representative of these developments is the still increasing number of foundries, where various customer products are fabricated. Typically, the optimization of these production processes is vital for staying competitive in the globalized industrial environment [CM16]. For this, a large range of different KPIs [HS01] are available to define and analyze the performance of the manufacturing environment. Typical reporting and analysis environments in today’s manufacturing environments often present and use historical data and are produced within defined time intervals, such as per shift or per day [GL16]. Therefore, reaction time to the shop floor is still too long [CM16].

In today’s digitalization processes, the real-time capability of data analysis and reaction becomes a vital element in facility optimization procedures. Within this environment, short and long-term predictions of different KPIs get more and more important. Different typical use cases can be further supported and optimized with reliable and real-time capable short-term forecasts, e.g. bottleneck management or maintenance schedule planning.

In the past and today, simulation is one of the still growing techniques to identify, analyze and forecast complex production environments. Banks [BAN07] proposed simulation to be “consistently one of the top three methodologies used by industrial engineers, management scientists, and operations research”. Nevertheless, in most cases simulation is not real-time capable and requires many pre-processed data in order to produce sufficient results.

In this paper, we present different results and ways to generate trustworthy KPI forecasts with statistical methods, like time-series analysis or neural networks based on the real-time capable data sources of the concept presented in [GL15A, GL15B].

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Description

Based on the real-time data aggregation approach (see [GL14]) different data sets are immediately available for KPI calculation. Besides the atomic data, which is the event-corresponding raw data, aggregated data layers are available (e.g. see event model in **Figure 1**). Such data can be e.g. fundamentals (defined time portions) or fractals (calculated time-based averages, like hourly throughput).

The time horizon and data granularity of the prediction depend on the defined use cases. Within our investigations, we started by using a continuous KPI like the WIP (Work in Process) for detailed research. Several use cases can be fulfilled by offering a detailed real-time capable forecast of the WIP, e.g. detailed maintenance planning or WIP balancing. A time-period based forecast of the WIP (e.g. hourly or minutely) fits the most use cases. We focus on the hourly WIP within defined filter criteria, like the equipment or the operation and use the calculated data based on the fractal data like the follows:

$$WIP(t_1, t_2) = \sum_{Lot \in (t_1, t_2)} \frac{T_{Lot \in (t_1, t_2)}}{t_2 - t_1}$$

Figure 2 illustrates the calculation scheme based on a simple example. Each time amount a lot is situated at a tool, is related to the general calculation period.

The forecast algorithm is based on different general statistical approaches we want to compare and combine. Currently, there are investigations within the algorithms of

- Simple linear models
- Vector-auto regressive models (VAR)
- Multivariate adaptive regression (MAR)
- Neural networks (NN)

All algorithms are tested within different simulated and real manufacturing environments and their data.

Figure 3 illustrates the system architecture. Based on different events coming from a message bus infrastructure, the system queues the incoming events and processes them for internal data aggregation and processing. The forecast component is divided into a model maintenance part (creating, learning, update) situated at the database itself and a model execution part, situated at the data processing part.

Innovation

Within the real-time ability of the proposed reporting environment, it is possible to feed and create valuable forecasts for continuous KPI, the work in process for example. The most data is extracted and aggregated by typical manufacturing events. The forecast itself is real-time capable and allows the support of different use cases situated at equipment maintenance, production control and optimization, as well as production planning.

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Results

As described, the different algorithms are tested with different simulated and real data environments and conditions. We see that simple linear models do not offer accurate forecasts. We enhanced the input by more influence variables, like the neighbor operations or processor or successor equipment. This data is extracted by using different causality analysis, e.g. via Granger test [G69]. One example of the results is illustrated in **Figure 4.**

The results of using a VAR model are more accurate. Different experiments shows a positive tendency. **Figure 5** shows an example of using real fab data with an 8hr forecast horizon. The error margin ranges between 20% and 60% depending on the type of equipment and their WIP situation. Neural networks also offer better performance in quality and time, depending on the right training data set. Here, the error margin ranges between 10% and 50%.

In general, the statistical forecast of manufacturing performance KPI offers large potential for realizing trustable and real-time capable predictions without using larger manufacturing simulation models or other techniques without real-time capability. Within our next steps, an implementation of a demonstrator environment is planned. Furthermore, other KPI, like Cycle Time or On-Time Delivery are part of current forecast investigations.

Pictures

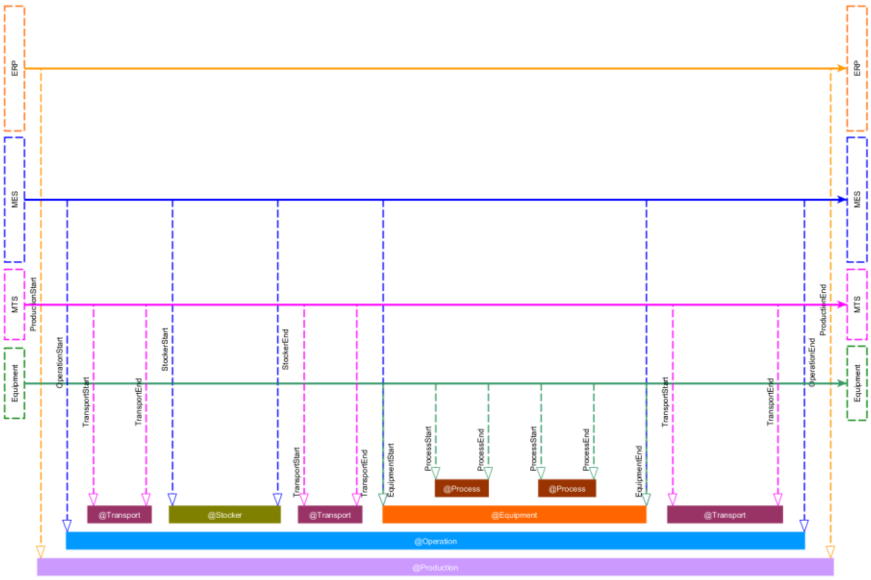

Figure 1 – Basic event model for lot movements and states

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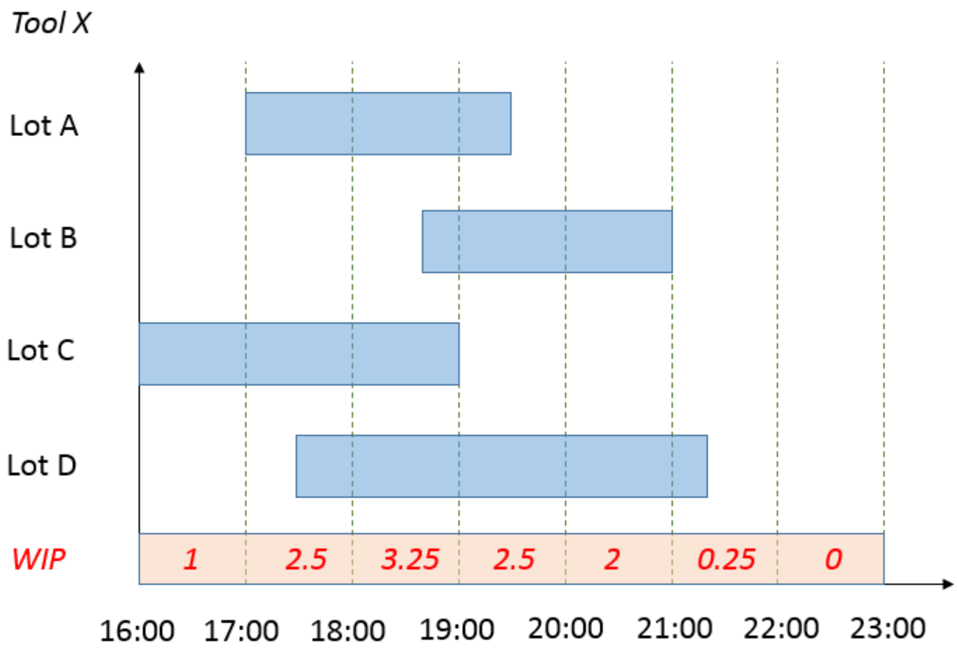

Figure 2 – WIP aggregation and calculation based on fractals – Example

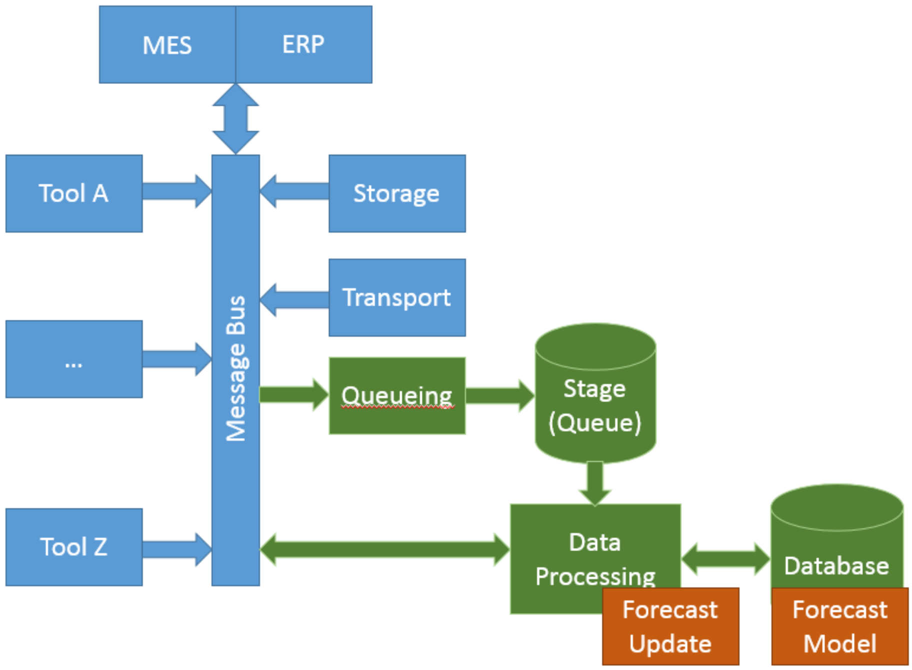

Figure 3 – System Architecture

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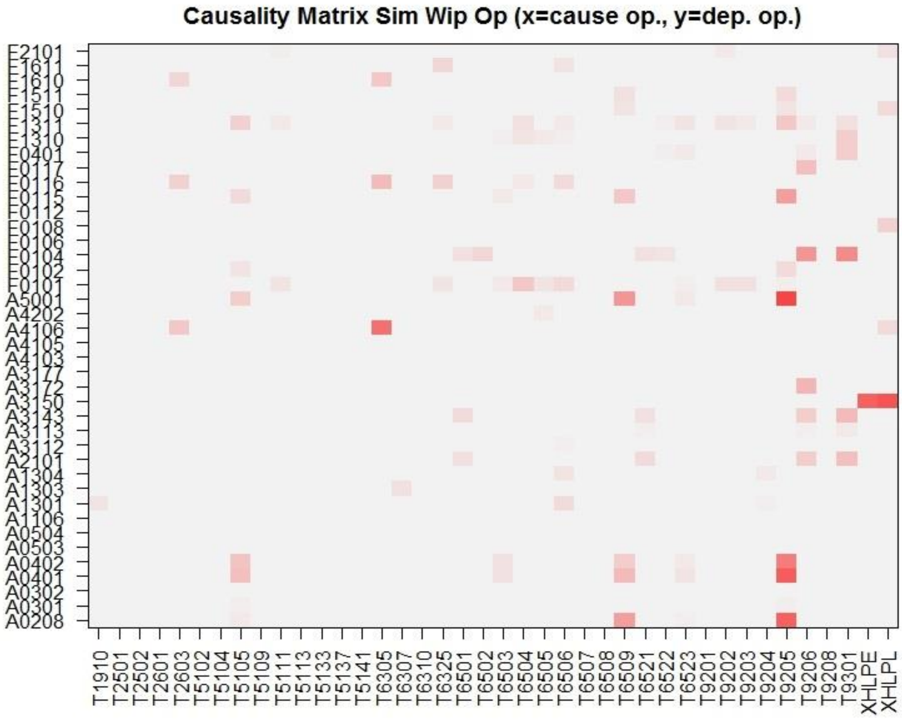

Figure 4 – Causality Matrix for Operations of Simulated Manufacturing Environment

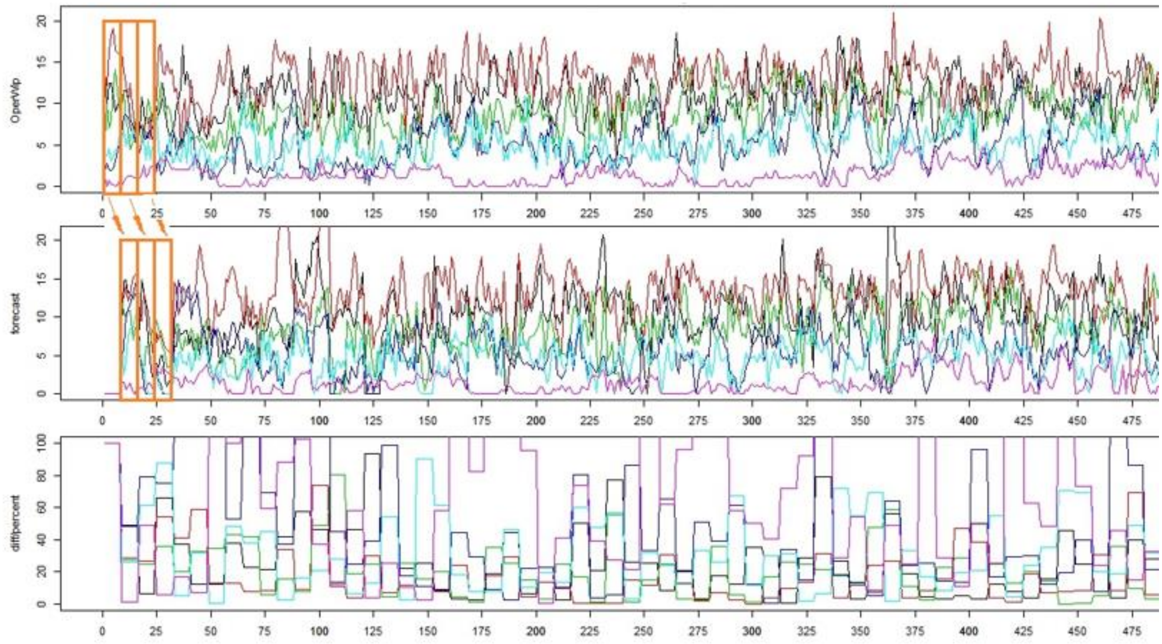

Figure 5 – Block wise calculation of forecast with 8hrs period with VAR

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