Proceedings of the 2020 Winter Simulation Conference
K.-H. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and R. Thiesing, eds.

CHALLENGES ASSOCIATED WITH REALIZATION OF LOT LEVEL FAB OUT FORECAST IN A GIGA WAFER FABRICATION PLANT

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ABSTRACT

In the semiconductor industry a reliable delivery forecast is helpful to optimize demand planning. Very often cycle time estimations for frontend, backend production, testing and transits are used to predict delivery times on product level and to determine when products have to be started to fulfill customer demands on time. Frontend production usually consumes a big part of the whole cycle time of a product. Therefore a reliable cycle time estimation for a frontend production is crucial for the accuracy of the overall cycle time prediction. We compare two different methods to predict cycle times and delivery forecasts on product and lot level for a frontend production: a Big Data approach, where historical data is analyzed to predict future behavior, and a fab simulation model.

1 INTRODUCTION

Demand planning is crucial for economic success. While this is true for any industry, maybe even more so for industries where the production process is complex and expensive. The semiconductor industry has typically a very complex production flow, consisting of frontend, backend, testing and storage facilities. Very often the facilities are not only logically but also physically distributed around the world. Additionally increasing number of products, requiring different production steps, can be ordered by customers. A lot of challenging task derive from that. Accepting or rejecting new customer orders, decisions when to start products and at which facility, confirming delivery dates or communicating expected delays, creation of stock piles along the supply chain are only some examples of tasks within the demand process. A reliable delivery forecast of products within the supply chain is helpful to make some of these tasks at least easier

(Nyhuis and Filho 2002; Geng and Jian 2009; Fowler et al. 2015; Seidel et al. 2017; Wang and Zhang 2016; Moyne and Iskandar 2017; Wang et al. 2018).

. At Infineon Technologies AG, a German semiconductor company, a simplistic approach of using the estimated cycle times to calculate the expected delivery dates on product level is typically used. The estimations are derived by analyzing historic cycle times. Sometimes time buffers are added or stock piles are created to ensure that due dates can be fulfilled. Boundary conditions can change of course, e.g. a frontend production can be overloaded, therefore the cycle time increases and predicted cycle times can no longer be met. A cycle time prediction by using a simulation model of a frontend production could help to mitigate this problem.

We decided to use the existing simulation models from different Infineon frontend production sites to predict product cycle times and lot delivery dates. We compared the simulation results with a Big Data approach and later on with the reality.

In Section 2 we provide some more details why a forecast could generate a benefit. Section 3 describes the simulation and Big Data approach and specifies our result comparison. In Section 4 we present the results and Section 5 gives a conclusion and an outlook of possible further studies.

2 BENEFIT OF A FORECAST

Demand planning at a frontend production site requires often manually effort, especially in situations where the demand is higher than the supply. Urgently needed products are sometimes tracked on lot level. Line control experts are busy tracking down and prioritizing lots to ensure on time delivery or at least minimizing expected delays. In the last years this task got more and more complex and time consuming because the number of products increased and often there was a shortage for many products simultaneously. For high volume products, lot priority lists changed daily because lots of the same product could overtake each other and therefore lot demand assignments changed overnight. Low volume products had to be prioritized after line incidents, e.g. a lot scrap or line performance issues. But updating these lists and changing priorities daily creates disturbances in the line, not to mention the psychological effect on people chasing the lots. Additionally it is well known that a high share of priority lots can cause line performance losses.

A reliable lot and product delivery forecast can help to reduce the prioritized lot count, the daily changes and therefore also manual effort from planner and line experts. A decisive question is how good a forecast can predict fab out dates on lot level or predict fab out on product level. Only if we know the answer to these questions we can try to estimate possible benefits.

3 APPROACHES FOR LOT LEVEL FORECAST

3.1 Discrete Event Simulation

Discrete event simulation has widely been used in the semiconductor industry for operational use cases such as early warning on forecasted WIP (work-in-progress) piling at production areas, allocation of operator resources based on forecasted incoming WIPs, preventive maintenance scheduling at the right time, dynamic dedication adjustment to minimize non-value add setup switching, and many more (Scholl et. al. 2011, Scholl et. al. 2012, Seidel et. al. 2017, Scholl et. al. 2018, and Seidel et. al. 2018). The aim has been to shift the production control paradigm from a purely reactive approach to a proactive approach, avoiding (minimizing impact) of problems instead of fixing them only when the problems occur. Ultimately, such a proactive operation management approach would help to improve the linearity of the production lines, which in turn reduces the cycle time variability, and thus enhance predictability of the fab performance.

The use cases thus far has been focusing primarily on aggregated KPIs (key performance indicators), which could achieve high accuracy. Based on our experiences, the forecast accuracy (Seidel et. al. 2017 and Mosinski et. al. 2017) for fab level KPIs such as wafer out, WIPs, moves, and cycle time or dynamic flow factor, could go as high as 95%. The forecast accuracy for product level KPIs stay at approximately

95% for high volume products, and drops to around 70% for very low volume products (products with less than ten lots throughout the 8 weeks forecast period). The high forecast accuracy could be achieved with the precondition of good input data to the simulation model. Table 1 and Table 2 below give a summary overview of the modelling elements and the modelling fidelity required to achieve the forecast accuracy as described. The simulation model was built on a commercial simulation engine, D-SIMCON Forecaster (D-SIMLAB Technologies 2020) that provides all the essential wafer fab modelling elements.

Table 1: Modelling Elements and Considerations for High Accuracy Forecast A.

Modelling Element	**Description**
Work-In-Progress (WIP)	The model is initialized with WIP in the production line, with all the lots and their associated information being captured. The essential lot information are its current step, current state: in queue, in process (current equipment and remaining processing time is required), in rework, or on-hold (estimated hold release time is required), priority, start and due date.
Initial Equipment Down	All equipment that are in down or non-productive state are initialized as down before simulation starts. An estimation of when the equipment is coming back online is required. This information is obtained from either historical data (average duration for the corresponding down type) or provided by the maintenance department.
Wafer Start Plan	A wafer start plan up to the lot level is required. Typically wafer fabs do not have lot level wafer start plan beyond a week. To address this constraint, a product level weekly volume start is obtained from the planning department, and a lot level wafer start plan is created. An algorithm of batching lots of the same product to start to enhance batching efficiency at furnaces is used for realistic wafer start plan generation.
Process Flows	All process flows required by the WIP and wafer start production lots are considered in the model. We do not choose representative process flows as we need to ensure lots are following the exact path that they will run in the reality.
Rework	Rework is modelled as a random event, where rework rate is derived from historical data for all production steps that could trigger a rework process.
Hold	Hold is modelled as a random event, where hold rate and hold duration distribution are derived from historical data for all production steps that could trigger lot hold.
Split-Merge	Some equipment type such as Chemical-Mechanical-Polishing (CMP) and Lithography require pilot runs from time to time. This is modelled with the split-merge function, where split rate is calculated from historical data.

In this paper, we would like to evaluate the accuracy that we could achieve in a lot-level fab out forecast using the same simulation model that was built for the operational use cases discussed above. We used the same simulation model to support the use case of development lot level journey forecast (Scholl et. al. 2016), and managed to achieve high accuracy as development lot was moved through the fab with higher level of priority than normal lots. It is easier to forecast because these higher priority development lots always overtake normal production lots. Dispatching will thus have much less impact in influencing the lot journey through the fab. Extending the lot level forecast to all production lots post a very different challenge even though the focus of the use case is only at the fab out date and not the day at which the lot will be arriving at each production step. Choice of lot selection at each dispatching decision could change the fab out date, and random events of hold/rework could significantly influence the cycle time of the lot. The good news is, our end user (demand fulfillment planner) does not require a forecast accuracy of up to daily granularity. A lot level fab out forecast for weekly time buckets will already be sufficient to create high values and benefits to them. Now, the remaining question is whether simulation model is able to enable such use case, and whether a combination with a Big Data approach will be a better solution.

Table 2: Modelling Elements and Considerations for High Accuracy Forecast B.

Modelling Element	Description
Equipment	All equipment in the production line are considered. Each equipment is mapped based on its specific behavior such as: single lot, single wafer, batch, or cluster.
Dedication	Dedication is modeled at recipe and product-recipe combinations, depending on equipment type. Long term inhibits are also considered in the model to ensure constraint in production line are portrayed accurately in the simulation model.
Process Time and Throughput	We gather data for recipe or recipe-product based process time and throughput for each equipment. Process time is defined as the time duration that lots/batches are spending in the equipment, while throughput is defined as the rate at which lots/batches are processed by the tools. Cascading of lots/batches are thus modelled when the throughput is higher than the process time. Limping effect (losing process speed) of chamber down is also modelled.
Setup Switching	Setup switching is modelled at some of the relevant equipment, such as implantation. We consider the time required to switch from one recipe class to another. This overhead is important to be modelled as it reduces the tool capacity.
Equipment Down	Equipment down is modelled as random event, where the mean time to failure and mean time to repair distribution are derived from historical data.
Reticle	Reticle is modelled as an additional resource required before lots can start processing at lithography equipment. This is essential because lithography equipment are typically the key bottleneck of the production line, and reticle availability could alter the lot selection for processing.
Dispatch Rules	Only global dispatch rules are considered in the model, such as lot priority, queue time priority, operation due date, maximum wait time and same setup. Some local dispatch rules such as prefer fast equipment were also considered.
Queue Time Constraint	Typically queue time constraint is controlled with KANBAN based dispatch rules. It is thus essential to construct a simulation model with such consideration as lots could be held back and not moving to the next step due to unavailability of KANBAN even though equipment capacity is available.

3.2 Big Data

Big data analytic or often referred as big data had been developed and applied in semiconductor manufacturing operations in recent years, such as fault detection (Chien et al. 2014; Chen et al. 2017), predictive maintenance (Lee at al. 2017) and forecasting cycle time (Wang and Zhang 2016). The evolution of big data had been developed with data peculiarities, in terms of volume, velocity, variety, veracity and value (Wang and Zhang 2016; Moyne and Iskandar 2017; Lee et al. 2017).With the massive semiconductors manufacturing data, data will be stored in a staging areas of data analytic tools before data analysis. Different types or combination of data analysis such as data mining, predictive analysis, machine learning or deep learning will be provided according to corresponding data analytic tools packages.

In this paper, Hadoop cluster had been chosen as data analytic tools for our study. Basis for the Big Data approach on lot level forecast is a data table which holds all transactions lots do see while they are processed in frontend facilities. The number of rows in such table, where each row is a transaction, is more than 200.000.000 for one year of data for several facilities. Such data table is updated daily from local data warehouses. It is hold by a Big Data datalake and investigated by a Hadoop cluster. Data analytics on such table is done by Spark SQL.

The main transactions are the move-out from the previous operation and the move-in to this operation. Different lots of different products do see different operations. Depending on the complexity of the product it is typically several 100 to more than 1000 operations for a lot in a frontend facility. The operation number is unique in the sequence of the operations for one lot.

Therefore for each lot, which left the facility already it can be aggregated how much time it took from each operation to the leaving of the facility. This is the remaining cycle time the lot had, when it was on such operation.

For a given product all the lots of such product can be used to make up a distribution of remaining cycle times for each operation. In Spark SQL it is straight forward to aggregate such distributions for all operations on all products. This distributions of remaining cycle times then can be used to forecast the time, when the facility will deliver such lot as a function of at which operation the lot currently is.

To some extent also the actual overall speed performance of the facility can be taken into account, to become more independent from the overall loading situation.

The accuracy of such prediction mainly depends on the level at which the aggregation of the distributions is calculated. We typically obtained a relative error of 8% for remaining lot cycle time over the complete life cycle of a lot.

3.3 Qualitative Comparison of Approaches

Both approaches have their strengths and weaknesses. The big data approach is easy to use and after the initial setup phase the effort to maintain it is small. However there are limitations to overcome. The impact of changing boundary conditions on product cycle time, caused by e.g. a ramping fab, a changing product mix, new incoming equipment or a change in tool dedications will be not reflected or only after some time because historical data will be not related to this new environment. For new products no historical data will be available at all.

While there are some ideas to mitigate this risk, e.g. use historical data from a similar product like the new one and use speed factors to incorporate actual fab performance, this will be a tough challenge to solve. Furthermore these mitigation strategies will increase the maintenance effort of the big data approach.

Maintaining a reliable simulation model creates a lot of effort. Data must be very accurate. Constant model validation is required. One bottleneck in simulation caused by wrong input data, not tally with reality, can jeopardize all simulation results.

On the other hand a reliable simulation model can forecast product cycle time changes over time due to changing environment. New product cycle time can be predicted even if no historical data is available.

Forecast accuracy comparison is done in section 4.3.

4 EXPERIMENTAL RESULTS

4.1 Forecast Quality Measurement for simulation

To evaluate the usability of the lot level fab out forecast with simulation, we need to measure the achievable forecast quality. This was done by choosing a high volume time period in the past, and running the simulation forecast to obtain each lot fab out week, and then compare with the actual fab out week. The forecast quality was measured in two perspectives: (i) lot level, and (ii) product group, as respectively illustrated in the equations below:

$$lot\ level\ forecast\ quality\ for\ n\ weeks = \frac{no\ of\ lots\ fab\ out\ in\ simulation\ and\ reailty\ in\ the\ same\ week}{no\ of\ lots\ fab\ out\ for\ evaluation\ period}, where\ w\ is\ the\ week$$

$$product\ level\ forecast\ quality\ for\ n\ weeks = \frac{\sum_{w=1}^{n} \frac{no\ of\ lots\ fab\ out\ in\ simulation\ and\ reality\ (w,p)}{no\ of\ lots\ fab\ out\ (w,p)}}{n}, where\ w\ is\ the\ week, and\ p\ is\ the\ product$$

The lot level forecast quality is measuring the accuracy of forecasting the same weeks in which the lots are being fab out in both simulation and reality. A high accuracy at the lot level forecast is the most stringent measurement, and could provide us an insight into the usability/applicability of providing such forecast to the end users.

The product forecast quality is measuring the accuracy of forecasting the fab out volume for each product, and aggregated across weeks with a simple average. We did not make an weighted average calculation across weeks as the product mix was stable for the chosen time period of the study. The product forecast is an alternative forecast granularity that we were exploring to provide to the end user because in a typical business process, our end users are matching the lots to a demand order upon fab out. The demand lot assignment is usually not fixed and can be changed over time. Some flexibility of reallocation of fab out lots to orders is still possible. This is an important point because it is possible that during simulation run, the random events such as rework and hold could extend some specific lots fab out time, or vice versa. This is also one of the key reasons, that high accuracy at lot level forecast is not easy to achieve.

4.2 Forecast Quality Comparison: Actual Wafer Start vs Plan Wafer Start

The accuracy of a simulation forecast is highly influenced by the approach being taken to model various aspects of the wafer fab. Equally important, the simulation model needs to be fed with good quality input data. For a use case such as the fab out forecast, an accurate wafer start plan is thus crucial. In fact, obtaining a high accuracy wafer start plan is posing an additional challenge to achieve good forecast quality. Typically wafer fabs only have high accuracy wafer start plan for one to two weeks. Any weeks beyond that are still volatile and subject to further changes. Thus, besides comparing the achievable forecast quality at lot and product level, we extend the experimental study to compare scenarios with and without high accuracy wafer start plan. This is possible to be conducted as we have chosen a historical time period where we already know which lots have been started, and we also know the wafer start plan available at the beginning of the evaluation period. The forecast quality data was collected for a time period of 8 weeks, as this is the required forecast time horizon by the end users.

Table 3: Actual vs Plan Wafer Start Lot Level Forecast Quality.

Actual Wafer Start	Plan Wafer Start
50%	46%

Table 4: Actual vs Plan Wafer Start Forecasted Day Gap.

Forecasted Days Gap	Actual Wafer Start	Plan Wafer Start
=0	10.0%	9.2%
<=1	25.9%	25.1%
<=2	40.4%	38.1%
<=3	52.9%	49.3%
<=4	62.9%	59.1%
<=5	70.8%	66.9%
<=6	77.7%	73.1%
<=7	82.1%	78.0%

Table 3 shows the lot level forecast quality achieved with simulation using the actual and plan wafer start. The actual wafer start forecast provided a 4% better forecast quality as compared to the plan wafer start. This forecast percentage is not very encouraging as it seems to indicate that we cannot use the simulation approach for lot level forecast use case. We thus add on an additional dimension in evaluating the applicability of the approach, to measure how much was the absolute deviation (in days) between the forecast and actual fab out day.

Table **4** shows the summary of this comparison. We observed that for 10.0% and 9.2% of the cases the fab out day in simulation and reality is exactly the same, using the actual and plan wafer start respectively. For 82.1% and 78.0% of the lots we saw a maximum gap of 7 days between simulation and reality. This means that the forecast could still be useful (but not ideal) for the end users because for approximately 80% of the cases they can be sure that lots will fab out within plus/minus 7 days of the forecasted value.

Figure 1 shows the forecast quality achieved for product groups, sorted from highest to lowest volume. We presented the forecast quality at product group level instead of the product level because the number of products involved are more than 200 and it is not feasible to show them in a single chart. The product group forecast quality was calculated as a weighted average (by the product volume of the week) of the product forecast quality. As observed, high volume product groups (first two product groups) achieved a forecast quality of above 90% for the runs with actual wafer start, and above 85% was achieved for the runs with plan wafer start. The forecast quality is steady between 78% and 75% for the next 11 product groups for runs with actual and plan wafer start respectively. Some of the extremely low volume products have shown very low forecast quality for plan wafer start. This is due to the fact that planed lot starts for low volume products are typically prone to high error. The observation for the product (group) level forecast quality is encouraging and shows that simulation can be used to forecast weekly product fab out with acceptable accuracy.

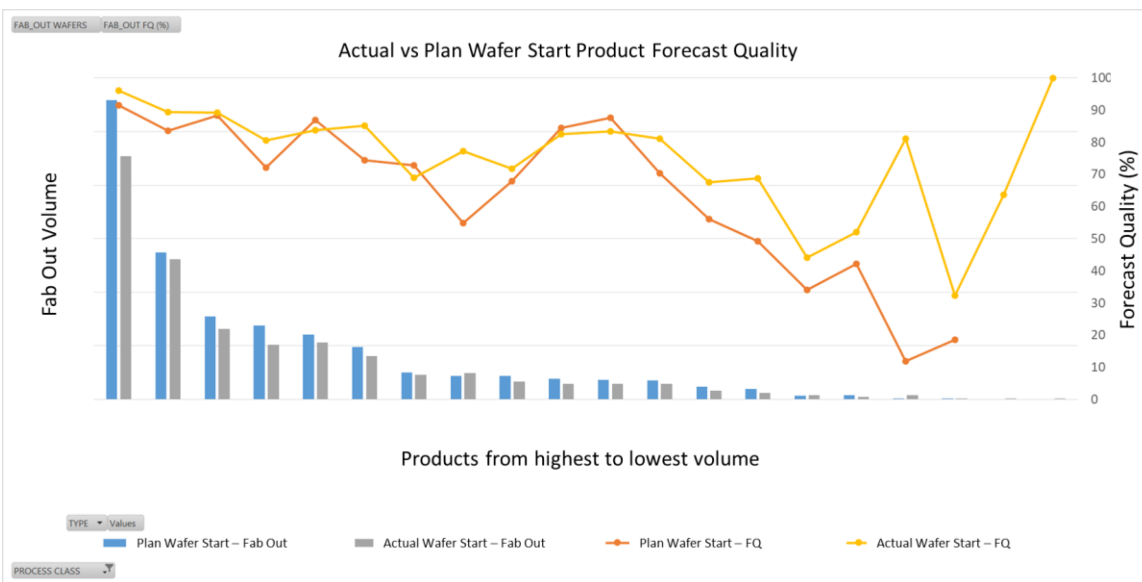


Figure 1: Actual vs Plan Wafer Start Forecast Quality Comparison.

4.3 Simulation vs Big Data Comparison

We compared the forecasts of two different fab simulation models with big data results. One was a validated fab simulation model from an Infineon frontend facility in Europe, and the other one a validated simulation model from an Infineon frontend facility in Asia.

Figure 2 shows the gap between the forecasted remaining cycle time and the real remaining cycle time for the European fab. Each data point represents the deviation for one lot. The lots are put in weekly buckets, dependent on the real remaining cycle time of the lots. Meaning that data points in the first box plot of the figure are representing lots where the remaining cycle time has been below 7 days in respect to the simulation start period. The upper part shows the results for big data, and the lower part for simulation. Coloring indicates the deviation between forecasted value and reality. Red indicates a higher gap percentage wise than green. The ideal result for a lot would be a dot with y value 0, indicating that the forecast met reality exactly.

As you can see simulation showed better results within the first weeks of the forecasting period. Big data overestimated remaining cycle time at the beginning, simulation underestimated cycle time at the end of the forecast period slightly more than big data. The underestimation of cycle time with the simulation approach is caused by missing line disturbance modelling elements such as operator and production interference of changing lots priority. This could be mitigated through enhancement of the simulation model prior to delivery of the use case to the end users.

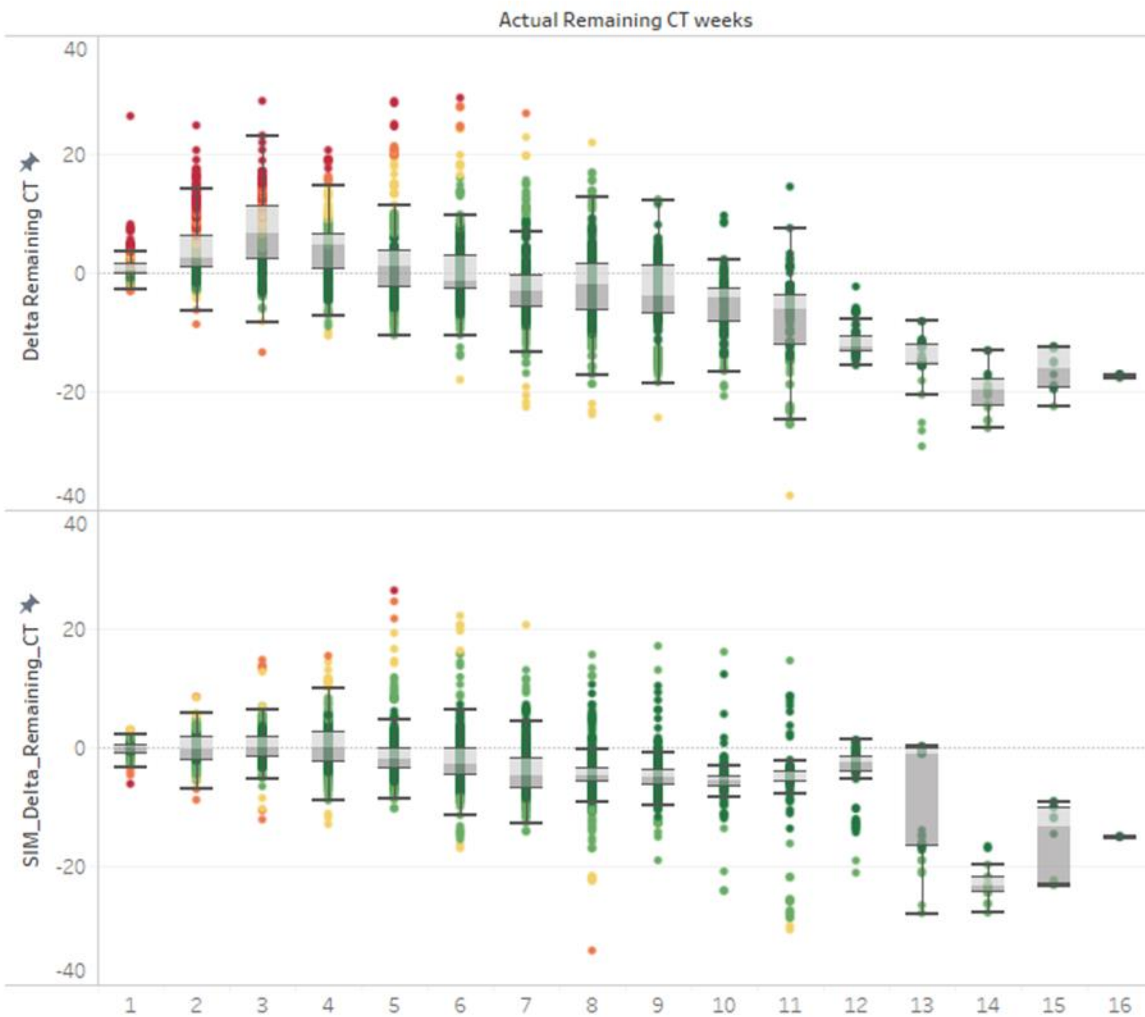
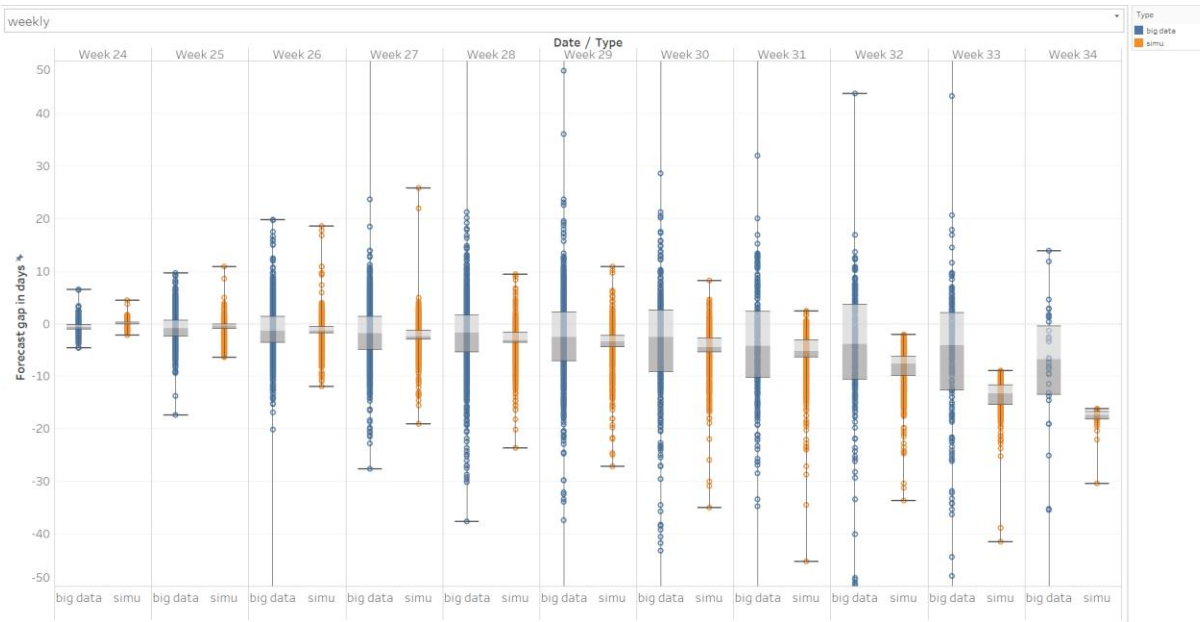


Figure 2:Cycle time forecast deviation for an European frontend site (big data upper part, simulation lower part).

Figure 3 shows a similar box plots for the results from the Asian frontend facility. You can see the weekly buckets again. The two leftmost boxplots show the results for all lots that finished processing within the first week after the simulation period (remaining cycle time was less than 7 days). Each dot represents a lot again. The blue boxplot represents results from big data, the orange one from simulation. The results



are similar for both frontend sites. Simulation prediction is more accurate at the beginning of the forecasting period. After some weeks simulation predicts shorter cycle times than reality, the same for big data but not as strongly.

Figure 3: Cycle time forecast deviation for an Asian frontend site (big data blue boxplots, simulation orange boxplots).

Figure 4: Correlation of big data and simulation forecast for an European frontend site.

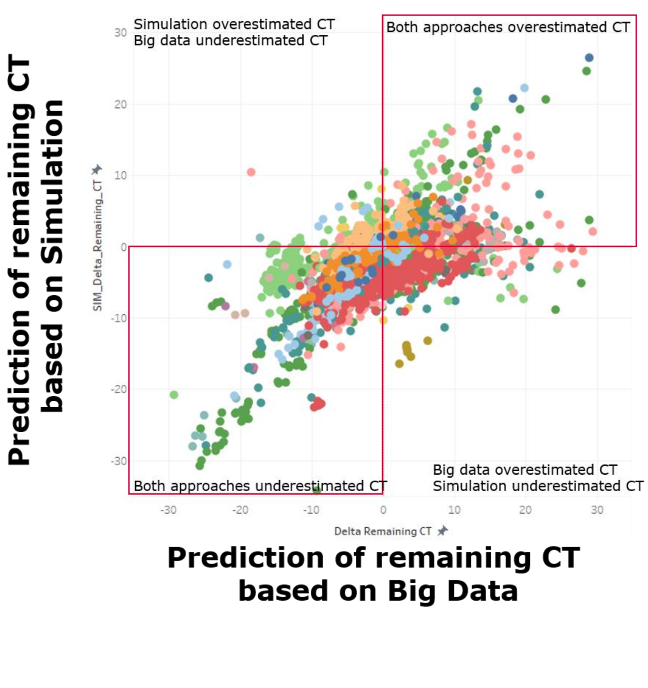


Figure 4 shows correlation of big data and simulation forecasting. Each dot represents the data for a lot. If the forecast is 100% accurate for both simulation and big data the data point sits right in the middle of the graphic. If the simulation predicts a higher/lower cycle time for the lot than observed in reality the data point will have a bigger/lesser y-value and if big data predicts a higher/lower cycle time for the lot the x-value of the data point will be bigger/lesser. Coloring of data points indicates different product classes.

You can observe a clustering of data points along the diagonal. This implies that for some lots cycle time predictions are tough to make. E.g. lots going on hold or a change of lot priorities unknown at the simulation start will be impossible to predict, no matter which method you use.

Accuracy of cycle time predictions can be dependent on process classes too as you can see in figure 4. For some product classes the spread of data points is higher than for others.

5 CONCLUSIONS AND FUTURE WORKS

Based on our study, the simulation forecast results have been slightly better than big data forecast results. Big data has the advantage of less effort to generate predictions. We are working on improving both methods. Simulation tends to underestimate cycle times because the simulation model is too fast. Disturbances in the fab like e.g. lots are waiting for operator to load equipment are not considered in our models yet.

Big data can be improved by adding factors to incorporate actual fab performance. One idea is to combine both methods in the future. Prediction of future fab performance can be done once a week by a simulation run. These results can be used as factor for big data.

This approach can reduce the effort for simulation because a weekly simulation run is sufficient. Big data can be used for daily predictions. The question of whether this can improve forecast results and reduces the effort to generate the forecasts will be part of future studies.

ACKNOWLEDGMENTS

We would like to thank our colleagues in contributing towards the successful completion of this work. They are Mr Patrick Preuss, Mr Chew Wye Chan, and Ms Xiaoqing Yang.

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