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DISCRETE EVENT SIMULATION IN SUPPLY CHAIN PLANNING AND INVENTORY CONTROL AT FREESCALE SEMICONDUCTOR, INC.

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ABSTRACT

The supply chain of Freescale Semiconductor from fabrication through final test and delivery was modeled and analyzed using discrete event simulation in Arena. Freescale starts products in manufacturing based on a make-to-order and make-to-stock master production schedule. Since customer lead time is often less than the supply chain cycle time, Freescale maintains strategic safety stock throughout the supply chain and as finished goods inventory. Manufacturing entry rate is determined by the amount of product in WIP and inventory. Our analysis concentrates on the relationship between on-time delivery in the major supply chain segments and on-time delivery to the customer in an environment of significant inventory and WIP level changes. The goal is to predict the effect of internal on-time delivery, inventory and WIP changes on the customer order fulfillment service level. In our analysis, we evaluate supply chain production and inventory control policies and the impact of lead time reductions.

1 INTRODUCTION

Freescale Semiconductor, Inc. is a global semiconductor company focused on providing embedded processing and connectivity products to large, high-growth markets. The company provides products to the automotive, networking and wireless communications industries. Freescale offers families of embedded processors, which provide the basic intelligence for electronic devices and can be programmed to address specific applications or functions, as well as a broad portfolio of complementary devices that provide connectivity between products, across networks and to real-world signals, such as sound, vibration and pressure. Through its embedded processors and complementary products, Freescale is able to offer customers platform-level products. On October 6, 2003, Freescale was created when Motorola announced its intention to separate its semiconductor operations into a separate company. In late 2004, it was spun off and Motorola ceased to be a controlling stockholder.

The semiconductor industry is a rapidly changing industry with shortening life cycles, fluctuating demand and continuous price and cost pressures. To keep up with this dynamic environment, a company must be flexible in the quantity and type of product kept in inventory. On hand inventory loses value quickly and in contrast, not enough inventory can lead to stock outs and late deliveries. Therefore, there is an on going balance in the industry between minimizing inventory and keeping on time service levels at an optimum point. Additionally, a company must be able to predict with a reasonable degree of certainty the result of changes in this balance and the impact on customer delivery.

When modeling a complex process such as manufacturing and assembly supply chain, it is best to start as simple as possible and expand only as necessary. With this in mind, the objective was to create a model that is as accurate and simple as possible to drive ease and flexibility of use. The model in this application is used for aggregate level inventory planning in the supply chain. Hence, rather than considering hundreds of individual SKU's, modeling is done at an aggregate level thus eliminating several layers of data and modeling complexity. The resultant model is a queuing-based simulation that approximates various elements of a semi-conductor supply chain in order to capture the aggregate level inventory behavior and service levels. Other related work on semiconductor supply chain production and inventory control that contains more detailed, complex, and sophisticated models is found in Braun et al. (2003), Vargas-Villamil et al. (2003), and Kempf (2004). For simplicity and specificity, we did not directly leverage this other work in our paper. However, we plan to consider certain aspects of it in our future work.

This simulation study has helped Freescale to better understand the relationship between inventory, internal on time delivery and customer delivery metrics. As a result, Freescale Semiconductor is more accurately able to model the result of operational decisions, predict the impact on customer on time delivery, and set the right expectations internally to drive supply chain behavior. This is critical for long lead-time supply chains such as those found in semi-conductor fabrication. Secondly, sensitivity analysis on fab lead times revealed a lead time reduction of 20% substantially improves service levels without a significant increase in inventory levels.

2 MODEL CREATION PROCESS

When creating this model, several steps had to be taken to accurately rationalize all of the processes and inventories. First, an outline of the supply chain needed to be created. This can be seen in Figure 1. This was done to develop and quantify the links between each process in the supply chain and their corresponding inventory amounts and impacts on customer delivery rates for Freescale. Once this is accomplished, each process can be broken down to obtain a more realistic model.

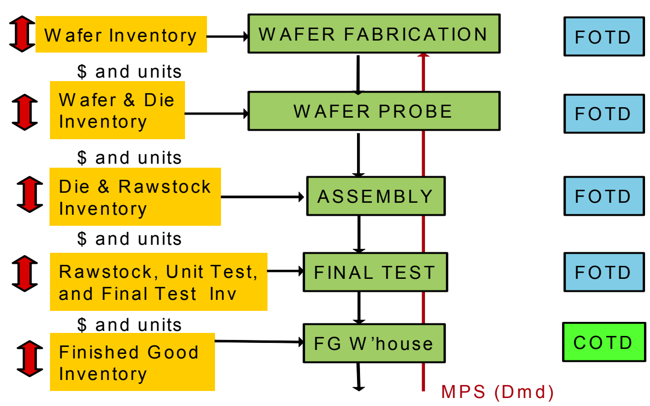

Figure 1: Overview of Freescale Supply Chain

Next, we needed to partition off the supply chain in order to better understand how all of the processes interact. There are two main divisions called the front end and back end. The front end consists of the wafer fabrication and wafer probe. At wafer probe, a wafer is subdivided into many die (die are the basic logic elements that used in computer chips and other electronic devices). The number of die per wafer varies based on the size of the wafer and percent of acceptable die (i.e., the yield percentage). Wafer sizes range from a few inches to a few feet in diameter and the yield percentage can vary between 80-90%. Note, in this study yield loss is ignored in order to reduce the complexity of the simulation model. In future work, we plan embellish the simulation model with more detail and add such things as yield loss (see Section 7 for more discussion on future work).

The back end consists of the assembly and final test processes. This is where the die is placed in a product, tested, and packaged to be a finished good. Both the front end and back end have a metric called Factory On Time Delivery (FOTD) to determine the on time service rates. There is an additional logistics process to deliver the finished goods and another metric to count on time delivery to customers called Customer On Time Delivery (COTD). The COTD is the most important metric in that it measures the total on time service rate to customers. These service level metrics are what we want to relate to inventory levels.

When the decision was made to create a simulation model, more detailed information was needed. This began with the front end which includes everything from manufacturing order creation through the die and rawstock inventory (see Figure 1 – this is also referred to as *die cage* inventory). Freescale provided data from the past year to show the times orders spent in front end. After eliminating outliers, a proper mean and standard deviation was found. This same reasoning was taken for all other processes. Data was gathered over the same time horizon from Freescale for each process and then rationalized to create distributions in the simulation model.

3 CONCEPTUAL DESCRIPTION OF THE SIMULATION MODEL

A conceptual overview of the simulation model of the supply chain is given in Figure 2. There are three main portions of the supply chain: front end (fabrication and wafer probe), back end (assembly and final test), and logistics. In front end, manufacturing orders are created and wafers are sent through the fab and probe to produce die. Back end takes the die matched with a projected customer order to create a fully functional product. Logistics takes the finished goods with a confirmed customer order to deliver the final product. Confirmed customer orders differ from projected customer orders due to order changes and demand fluctuations that occur over the period of time it takes for orders move through the back end of the supply chain.

There are two main inventories. The first is between die cage inventory between front end and back end: the second is the finished goods inventory located between back end and logistics. The other two inventories shown in Figure 1 between wafer fab and wafer probe and between assembly and final test are not explicitly represented in the model because they are much smaller inventories in practice due to the fact that these front end and back end activities are completed in pairs often in the same facilities.

Manufacturing orders are created on a constant basis everyday to approximate aggregate demand creating a constant flow of materials into the fabrication facility. While this is an approximation, it works well due to the level of aggregation and to the fact that manufacturing orders are released in controlled manner and are not subject to the same level of fluctuations as end customer demand. The manufacturing orders can be increased or decreased based on the size of inventory in the die cage waiting for customer orders as shown by the feedback loop in Figure 2.

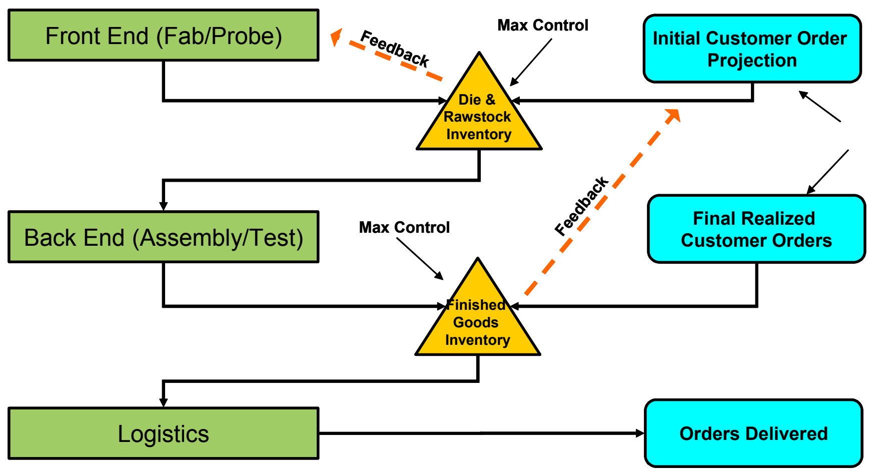

Figure 2: Overview of Simulation Model

When the orders reach the fabrication facility, they are processed (fabricated, probed, and then cut into die) and sent to the die cage inventory. The total amount of time orders spend in the front end of the supply chain was found to be approximately normally distributed. This distribution was created with the use of actual fabrication data from Freescale. All parts were aggregated and the distribution is representative of the entire inventory. On average, front end time represents about 80 percent of the total time orders spent in the supply chain. In the simulation, the time in the front end is recorded for each order and then it is compared to a benchmark set by Freescale to calculate front end FOTD. This benchmark is set such that order cycle time can be effectively compared to its planned time no matter the part. This also has been aggregated due to each part having a different planned cycle time.

Next, manufacturing orders are converted into the average equivalent number of customer orders. The conversion factor is randomly generated from a discrete probability distribution determined from Freescale historical data and expert opinion. These equivalent number of customer orders are matched with projected customer orders if the latter are waiting in backlog, else they are placed into the die cage as inventory to wait for matching with projected customer orders when the latter are generated at a later point in time. After this matching occurs, projected customer orders proceed to the back end stage. Projected customer orders are generated at a constant rate. Similar to manufacturing orders, this approximation is sufficient due to the level of aggregation and the somewhat controlled nature in which projected customer orders are released to the back end. It is important to note that that the stochastic nature of demand is accounted for in the deviation of final customer orders from projected customer orders at the end of the supply chain model. Based on historical data, this deviation was found to be approximately normally distributed with a coefficient of variation of about twelve percent.

As mentioned previously, the level of die cage inventory acts as a control on the rate at which manufacturing orders are released into the fab. If die cage inventory exceeds a certain maximum level (we will refer to this as MaxDieQueue for short) the release rate is decreased until the inventory drops back below MaxDieQueue. MaxDieQueue is a design parameter that is determined in our simulation analysis.

In the back end, the delay times for assembly and test are both modeled using triangular distributions. Parameters for these distributions were based on historical data and expert opinion. The latter was used because of the relatively short amount of time spent in these steps compared to fabrication. Also, assembly and test have little variations in time required to finish compared to that of fabrication and probe. The time taken from the creation of a projected customer order until it finishes back end is compared against a Freescale benchmark time to calculate back end FOTD.

After leaving back end, the projected customer order is either matched up with a waiting final customer order and shipped via logistics or it goes into finished goods inventory and waits to be matched to a final customer order. Again the discrepancy between projected and final customer orders is intended to represent supply/demand mismatches due to errors in forecasting random demand. Similar to the control defined by die cage inventory on the release rate of manufacturing orders, the level of finished goods inventory is used to control the release rate of projected customer orders (see Figure 2). In other words, this is used as a way of controlling mismatches between projected and final customer orders. Specifically, if finished goods inventory exceeds a certain maximum level (MaxFGIQueue), the release rate of projected customer orders is decreased until the inventory falls back below MaxFGIQueue. MaxFGIQueue is another design parameter that is determined in our simulation analysis.

The logistics stage is the process to get the matched customer orders and deliver them to the appropriate customers on time. For this logistics delay distribution, we used average delivery times from historical data. To ensure a tight controlled distribution, we used a triangular distribution that had a firm minimum and maximum based on expert opinion. Just before the model ends, the time from the creation of a final customer order to the end of the logistics step is compared against a benchmark time to calculate COTD.

It is interesting to note that this same model is simple and universal enough to be used to illustrate any large manufacturing process with several inventories and process stages.

4 ARENA MODEL

We implemented the simulation in Arena (Kelton et al. 2004). Figure 3 contains the process flow diagram. Following the logic of the process flow diagram, manufacturing orders are generated, processed in the fab, and then translated into the equivalent number of customer orders to form die inventory. When projected customer orders are generated, they are matched against die inventory and then proceed to assembly and test. After assembly and test, they become finished goods inventory where they are matched against final customer orders. Lastly, orders incur a logistics (shipping) delay before reaching the customer.

By three pairings of Assign/Record modules, the model captures the time in the back end of the supply chain, the time in the front end of the supply chain (i.e., from the time a projected customer order is generated until the order leaves assembly and test) , and the logistics lead time (i.e., from the time the final customer order is generated until the order is filled). These times are used to calculate the aforementioned service delivery statistics.

Manufacturing orders and projected customer orders are released at a constant rate. Manufacturing order releases are controlled by the amount of inventory in the die inventory order match queue. Similarly, projected customer order releases are controlled by the amount of inventory in the final order match queue. Final customer orders are generated randomly to represent the stochastic nature of demand. Random delays occur at the fab, assembly, test, and logistics.

5 SIMULATION EXPERIMENT

One of the main objectives of this simulation study for Freescale was to understand how they might control order release rates into the front end and back ends of the supply chain in order to reduce average inventory levels and maintain desired service levels. To do this, we ran sensitivity analysis on MaxDieQueue and MaxFGIQueue. Note that we did not consider sensitivity analysis on the amount by which release rates change because these amounts were not considered to be highly flexible in practice. In other words, there are certain discrete amounts by which these quantities can be realistically changed.

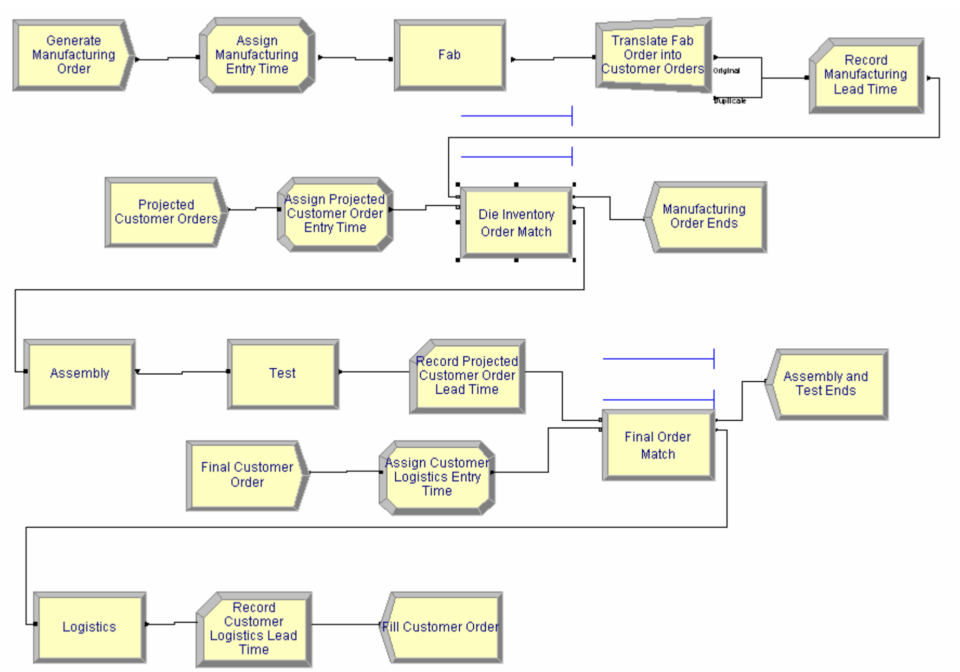

Figure 3: Arena Simulation Model of Freescale’s Supply Chain

Further experimentation considered the impact on inventories and service levels of reducing average front end processing time. Front end processing time represents about 80 percent of total supply chain flow time. By reducing this time, we decrease the time necessary to correct shortages or stockpiles in inventory. Faster response time could lead to a change in average inventory needed to satisfy on time requirements. Front end processing time was changed through the introduction of a variable called FabTime which represents the mean number of days in the front end .

A scenario is defined by a specific set of values for the parameters. Ten simulation replications were made for each scenario in order to generate confidence intervals. Each replicate is simulated for ten years after a 300 day warm-up period. The warm-up period was chosen by visual inspection using an approach similar to Welch's procedure (Law and Kelton 2000). One additional measure was taken to reduce initialization bias in the statistics. The generation of the first projected and final customer orders were delayed by about the length of the average lead times from manufacturing order generation to each of these points in the process. This was done so that customer orders would not be generated and sit waiting, artificially biasing these queue statistics as the first manufacturing orders fill up the supply chain. By experimentation, we determined that a ten year simulation replication was sufficient because statistics had stabilized indicating that we were approximating long-run steady state results.

6 SIMULATION RESULTS

The simulation results that follow are illustrative of the type of analysis for which we used the model. We focused first on the parameters designed to control the order release rate, i.e., MaxDieQueue and MaxFGIQueue. After ranges were decided for each parameter, three equally spaced levels were assigned to each parameter. Some additional runs were made to illustrate the impact of additional inventories on the service levels and to demonstrate the impact of lead time reduction on both inventory and service levels.

Tables 1 and 2 contain queue statistics and service level statistics, respectively, generated by Arena. The scenarios are defined by the MaxDieQueue and MaxFGIQueue pair given in parentheses at the top of each column in both tables. For both inventory and backlog, Table 1 provides averages and half widths for a 95% confidence interval. Table 2 contains averages and standard deviations for the three classifications of service level: early, late, and on time. For front end FOTD, a combined early/on time percentage exceeding 90% is considered a minimum acceptable target level. For back end FOTD and COTD, on time percentages alone must exceed this minimum acceptable level because early delivery of product to either finished goods inventory or the customer are not considered acceptable.

Several patterns emerge from the data Tables 1 and 2, most of which are intuitive.

1. From Table 2, it is evident that front end FOTD exceeds minimum acceptable service levels and remains fairly constant across all scenarios. This is expected since MaxDieQueue and MaxFGIQueue impact queues following the front end.
2. As MaxDieQueue increases, the average level of die inventory increases, die backlog decreases, and back end FOTD improves. In general, inventory and backlog changes are statistically significant (as measured by non-overlapping confidence intervals). Back end FOTD becomes more consistent (standard deviation of back end FOTD decreases).
3. As MaxDieQueue increases, the average level of finished goods inventory generally increases and the order backlog generally decreases although the results are not statistically significant. Correspondingly, COTD on time percentages generally increase and become more consistent. Increasing MaxDieQueue indirectly impacts the finished goods metrics because as more front end inventory becomes available, front end customer orders are delayed less often and flow through to the back end more quickly.
4. As MaxFGIQueue increases, the general trend in is an increase in the average level of finished good inventory and a decrease in finished goods order backlog. However, statistical significance was not easy to establish because of the noise in this process. The additional noise is due to the aforementioned mismatch between supply and demand .

It is important to note that none of the scenarios considered thus far achieve a minimum acceptable COTD. Hence, we conducted two more simulation runs with MaxDieQueue and MaxFGIQueue pairs of (350,350) and (400, 400) (see Tables 3 and Tables 4). Scenario (400,400) achieves services levels exceeding 90% for all three stages. Additional simulation runs were made to with MaxDieQueue and MaxFGIQueue above 400 but it was found that inventory levels grew much more rapidly in order to get additional increases in service level.

Our last scenario shown in the last column of Tables 3 and 4 (denoted by "LT-20%" as the last term in the parentheses) considers a 20% reduction in front end lead time. A 10% reduction was considered but the results were not included because it did not have much on an impact on the statistics. A reduction of 20% was deemed to be the largest feasible reduction that could be considered at this time. Comparing these results with the corresponding scenario in Tables 1 and 2 without the lead time reduction (i.e., with

Table 1: Inventory and Backlog Queue Statistics for Main Scenarios

	Scenario	(200, 200)	(250, 200)	(300, 200)	(200, 250)	(250, 250)	(300, 250)	(200, 300)	(250, 300)	(300, 300)
Die Inventory	Average	123.97	158.62	201.32	121.70	160.13	200.16	121.45	161.60	202.84
	Half Width	2.84	5.82	6.81	4.51	7.04	8.29	4.30	4.91	6.49
Order Backlog for Die	Average	32.78	20.22	11.00	34.67	20.74	10.43	37.77	17.87	9.93
	Half Width	4.05	3.34	1.70	5.78	5.31	2.57	6.50	2.61	2.17
Finished Goods Inventory	Average	108.65	116.22	129.03	114.43	157.85	157.68	175.09	192.39	208.21
	Half Width	29.55	19.31	24.47	46.49	21.04	25.49	50.39	27.45	30.39
Order Backlog for Finished Goods	Average	41.20	21.43	18.73	61.78	15.14	14.69	41.19	13.69	12.96
	Half Width	40.66	8.70	13.08	49.26	7.24	14.23	40.79	10.52	11.18

Table 2: Service Level Statistics for Main Scenarios

	Scenario	(200, 200)	(250, 200)	(300, 200)	(200, 250)	(250, 250)	(300, 250)	(200, 300)	(250, 300)	(300, 300)
Front End FOTD										
Early	Average	38.039	37.904	38.045	37.909	37.918	38.024	37.925	37.913	38.222
	Stdev	0.407	0.527	0.456	0.476	0.352	0.362	0.468	0.318	0.400
Late	Average	8.791	8.864	8.955	8.888	8.957	9.056	8.978	9.128	8.882
	Stdev	0.223	0.363	0.237	0.228	0.352	0.220	0.294	0.260	0.197
On Time	Average	53.171	53.232	53.000	53.203	53.125	52.920	53.097	52.959	52.896
	Stdev	0.411	0.570	0.501	0.504	0.391	0.358	0.385	0.294	0.394
Back End FOTD										
Early	Average	3.424	3.759	4.039	3.398	3.752	4.076	3.335	3.823	4.085
	Stdev	0.147	0.118	0.120	0.229	0.215	0.141	0.228	0.118	0.145
Late	Average	11.337	7.749	5.208	11.939	7.858	5.127	12.766	7.101	4.980
	Stdev	1.727	1.384	0.611	2.363	2.100	0.947	2.511	0.998	0.840
On Time	Average	85.239	88.493	90.753	84.663	88.390	90.797	83.899	89.076	90.935
	Stdev	1.600	1.278	0.500	2.142	1.898	0.819	2.294	0.892	0.714
COTD										
Early	Average	1.469	1.597	1.661	1.294	1.703	1.748	1.509	1.734	1.754
	Stdev	0.454	0.178	0.241	0.551	0.150	0.222	0.476	0.211	0.191
Late	Average	21.529	14.848	12.152	30.453	10.154	9.062	20.789	9.081	8.478
	Stdev	22.860	7.445	10.679	27.479	6.345	10.677	23.578	9.294	8.629
On Time	Average	77.001	83.555	86.187	68.254	88.143	89.190	77.703	89.185	89.768
	Stdev	22.407	7.270	10.438	26.929	6.196	10.456	23.102	9.084	8.439

Table 3: Inventory and Backlog Queue Statistics for Additional Scenarios

	Scenario	(350, 350)	(400, 400)	(200, 200, LT-20%)
Die Inventory	Average	244.08	289.06	128.21
	Half Width	4.11	7.72	3.54
Order Backlog for Die	Average	4.61	2.16	16.79
	Half Width	1.32	0.67	1.83
Finished Goods Inventory	Average	230.54	280.68	123.89
	Half Width	34.19	25.51	15.94
Order Backlog for Finished Goods	Average	14.03	7.63	17.78
	Half Width	13.46	7.21	10.09

Table 4: Service Level Statistics for Additional Scenarios

	Scenario	(350, 350)	(400, 400)	(200, 200, LT-20%)
Front End FOTD				
Early	Average	37.696	38.150	37.755
	Stdev	0.458	0.459	0.479
Late	Average	8.845	8.794	8.924
	Stdev	0.226	0.245	0.247
On Time	Average	53.459	53.057	53.322
	Stdev	0.443	0.505	0.430
Back End FOTD				
Early	Average	4.318	4.406	3.847
	Stdev	0.087	0.059	0.107
Late	Average	3.619	3.027	6.691
	Stdev	0.482	0.179	0.626
On Time	Average	92.063	92.567	89.462
	Stdev	0.413	0.150	0.535
COTD				
Early	Average	1.769	1.836	1.669
	Stdev	0.236	0.106	0.171
Late	Average	8.350	4.802	11.395
	Stdev	10.701	4.872	7.385
On Time	Average	89.881	93.361	86.935
	Stdev	10.465	4.767	7.215

scenario (200, 200)) , it is evident that back end FOTD and COTD improve by shortening the front end lead time. The average level of die inventory has increased with the shortened lead time but not significantly. More importantly, the back end FOTD and COTD for the scenario (200, 200, LT-20%) are more comparable with scenarios (300, 200) or (250, 250) which hold a lot more inventory, especially in the die cage to achieve comparable service levels.

7 CONCLUSIONS

Simulation analysis permitted us to quantify/predict the effect of internal on time delivery, inventory and WIP change on the customer order fulfillment service level. In particular, it allowed us to establish appropriate control levels at various stages in a semi-conductor supply chain based on inventory and service level metrics. It also allowed us to explore the benefit of reducing front end lead times.

As part of future work, we intend to examine the benefit of including more detail in the simulation model without creating a model that becomes too cumbersome to analyze. This would include such things as adding more details in the various processes throughout the supply chain, incorporating yield losses, and considering finer levels of control more closely spaced throughout the supply chain. If possible, we intend to leverage some of the more sophisticated methods found in Braun et al. (2003), Vargas-Villamil et al. (2003), and Kempf (2004) without making the modeling and analysis overly-complex.

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