CASE 66

Fabrication Line Capacity Planning Using a Robust Design Dynamic Model

Abstract: We needed to expand a fabrication facility to increase production capacity. To clearly understand the various expansion alternatives, we evaluated the performance of fabrication line configurations according to how closely they followed the ideal dynamic relationship:

$$Y = (\text{lot start factor} + \text{workweek factor} \times M_2)M_1$$

where Y is the product ship rate (wafers/day), M_1 the lot start rate (lot starts/week), and M_2 the scheduled workweek (workdays/week).

We set up fabrication line simulations according to an L_{36} ($2^{11} \times 3^{12}$) inner array for configuration factors. We identified noise factors to evaluate robustness to workforce fluctuations, equipment availability, and operation protocols, and then selected worst- and best-case combinations. We simulated each combination of line configuration factors twice at each noise factor case for three workweek schedules and five lotstart rates. We determined an optimum line configuration by comparing ANOVA results for the lot start factor sensitivity and signal-to-noise (SN) ratio, and the workweek factor sensitivity and SN ratio calculated for each inner array row. We ran confirmation simulations for the optimum and a second (selected) configuration; the results agreed with linear predictions.

1. Introduction

We established a fabrication facility for accelerometer sensors, evolving from pilot line to moderate production levels. We now required a substantial increase in production capacity. To help define the equipment and workforce additions needed to maintain the target production levels, we used a simulation software package to model the fabrication line and robust design techniques to find an optimum stable configuration.

We developed a model of the present fabrication line and validated its behavior against our existing production history. We then developed a baseline expansion configuration using conventional capacity planning methods with our line production history data, tempered by space and budget constraints. We included the baseline as the initial (all level 1) control factor combination in this experiment.

Monitoring the stability of the sensor fabrication line (or a faithful simulation) involves tracking work-in-progress and scrap profiles, cycle and queue times, and other parameters. We defined an ideal function for the line that allowed more efficient evaluation of stability and capacity by focusing on one response parameter.

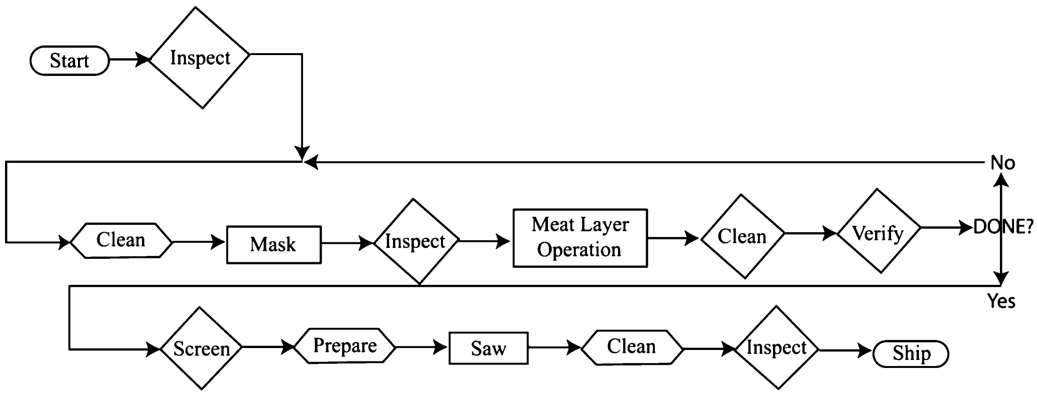

Figure 1
Flow diagram

2. Fabrication Line Model

The fabrication line model was constructed using Taylor II for Windows 4.20 [1], a menu-driven discrete-event simulation package. The Taylor II software features include predefined basic element types, integrated runtime animation, user-defined functions, and batch run mode.

The model has the following basic characteristics:

- The model was expanded from that implemented in an earlier study [2].
- Each in-line piece of equipment was represented; each task performed with the equipment was defined.
- Cycle times and variations were derived from operation standards and production history data.
- Conservative line loss (scrap) was modeled.
- Unit yield per wafer was considered constant.
- Automated operations were modeled in three parts: operator-assisted load, untended operation, and operator-assisted unload.
- Extra preparation time was included at the beginning of each process module.
- No mask step rework was included.
- End-of-shift protocols, operator task sharing, and maintenance events were not modeled directly. For simplicity, these were included as workforce and equipment availability variations combined into the outer array noise.

The process flow for the simulation model (Figure 1) was derived from the product traveler (the formal step-by-step definition of the process sequence). The accelerometer sensor fabrication process resembles semiconductor wafer fabrication in that many workstations (e.g., cleaning, masking, and inspection) are visited multiple times by a product wafer as it is processed to completion. The product wafers start in lots processed together until the structures are fully formed. They are then regrouped into smaller batches for the remaining "tail-end" processing.

The key response parameter of a fabrication line is the number of products shipped. The number of products shipped will ideally be proportional to the number of product lot starts for at least light-to-moderate production levels. The degree to which the product ship rate deviates from this proportionality defines the basic line stability. The onset of line saturation, when further increases in the rate of lot starts do not increase the rate of products shipped, defines line capacity. Therefore, we selected the lot start rate as the primary signal factor (M_1) for the fabrication ideal function.

We selected the strategy of changing the workweek schedule to adjust line capacity while keeping workforce and equipment constant. We included days per workweek as the second signal factor (M_2) to evaluate its effectiveness and sensitivity.

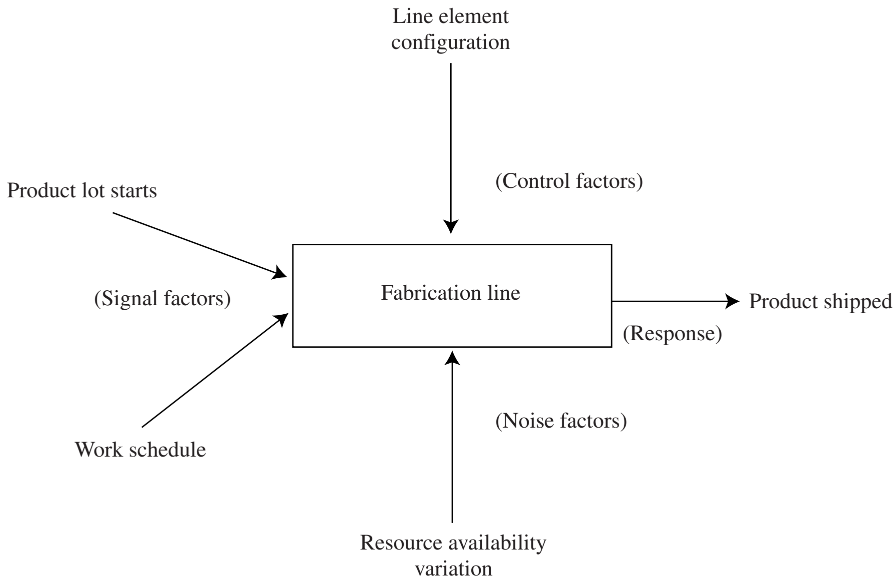

Figure 2
P-diagram

3. Design of Experiment

Figure 2 shows the P-diagram for the fabrication line ideal function. The zero-point proportional double dynamic model was selected to establish the product ship rate dependence on lot start rate (start none–ship none). The effect of varying the scheduled workweek was included as a modifier to the lot start rate coefficient in the form

$$Y = \beta_1 + \beta_2\ (M_2 - M_{20})\, M_1$$

where Y is the product ship rate (wafers/day), M_1 the lot start rate (lots/week), M_2 the scheduled workweek (workdays/week), M_{20} the nominal

Table 1
Signal and noise factors

	Factor	Description	Level Value	Level Code
M_1:	lot start rate (lots/week)	Number of product wafer lots started per week	2	2
			3	3
			4	4
			5	5
			6	6
M_2:	scheduled workweek (days/week)	Number of days per week scheduled for production shifts	5	−1
			6	0
			7	1
N:	noise	Combined variation in the availability of inspection stations, steppers, saws, and operators	Worst	−1
			Best	1

Table 2
Control factors

Factor		Level 1	Level 2	Level 3	Description
A:	meas	Baseline	Added	—	Number of verification measurement stations
B:	spcr1	Baseline	Added	—	Number of spcr1 stations
C:	spcr2	Baseline	Added	—	Number of spcr2 station
D:	etch 1	Baseline	Added	—	Number of etch1 stations
E:	etch2	Baseline	Added	—	Number of etch2 stations
F:	snsr1	Baseline	Added	—	Number of snsr1 stations
G:	snsr2	Baseline	Added	—	Number of snsr2 stations
H:	PC_cln	Baseline	Added	—	Number of pc cleaning baths
I:	D_cln	Baseline	Added	—	Number of d cleaning baths
J:	B_cln	Baseline	Added	—	Number of b cleaning baths
K:	oven	Baseline	Added	—	Number of curing/drying ovens
L:	metal_dep	A	B	C	Number and type of metal deposition systems
M:	coater	1+	2	3	Number of front-end coaters
N:	process	Baseline	Improved	Improved HD	Production process improvement strategies
O:	stepper	1	1+	2	Number of active steppers
P:	develop	1	2	3	Number of develop baths
Q:	descum	2	3	4	Number of descum units
R:	screen	2/1	2+/1+	3/2	Number of screening stations
S:	saw	1	2	3	Number of saws
T:	batch	s	m	1	Tail-end batch size
U:	staff	Base	Base+1	Base+2	Workforce staffing level
V:	empty				
W:	empty				

workweek (6 workdays/week), and β_1 and β_2 are sensitivity coefficients.

The noise cases were generated by combining values for the number of inspection stations, specific equipment availability, process module preparation time, and absenteeism, which were all "lean" for the worst case and all "augmented" for the best case. Each noise case was run twice to sample two simulation random number generator sequences.

The signal and noise factors are described in Table 1. Fully crossing the two signal factors with the noise cases required that 60 simulations be evaluated for each line configuration.

The inner array factors are described in Table 2. Control factors *A* to *K*, *M*, and *O* to *S* represent fabrication line elements viewed as determiners of production capacity. They were evaluated with baseline values as level 1 and augmented values as level 2 (and 3). Three strategies involving number and type of metal deposition systems used in the process were represented in factor *L*. Two process improvement strategies were compared with the current

Table 3
Inner array (L_{36}) response summary

	Factor																							Production Ship Rate			
No.	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*	*M*	*N*	*O*	*P*	*Q*	*R*	*S*	*T*	*U*	*V*	*W*	β_1	SN_1 (dB)	β_2	SN_2 (dB)
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1.314	−3.98	0.186	−20.95
2	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	1.580	0.22	0.239	−16.38
3	1	1	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3	3	3	3	3	3	1.602	1.48	0.220	−15.75
4	1	1	1	1	1	2	2	2	2	2	2	1	1	1	1	2	2	2	2	3	3	3	3	1.629	2.50	0.212	−15.21
5	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	3	3	3	3	1	1	1	1	1.329	−3.11	0.220	−18.72
6	1	1	1	1	1	1	2	2	2	2	2	3	3	3	3	1	1	1	1	2	2	2	2	1.472	−1.03	0.227	−17.27
7	1	1	2	2	2	1	1	1	2	2	2	1	1	2	3	1	2	3	3	1	2	2	3	1.73	0.39	0.254	−15.97
8	1	1	2	2	2	1	1	1	2	2	2	2	2	3	1	2	3	1	1	2	3	3	1	1.584	0.58	0.219	−16.59
9	1	1	2	2	2	1	1	1	2	2	2	3	3	1	2	3	1	2	2	3	1	1	2	1.265	−2.02	0.220	−17.22
10	1	2	1	2	2	1	2	2	1	1	2	1	1	3	2	1	3	2	3	2	1	3	2	1.300	−2.10	0213	−17.80
11	1	2	1	2	2	1	2	2	1	1	2	2	2	1	3	2	1	3	1	3	2	1	3	1.406	−1.07	0.226	−16.96
12	1	2	1	2	2	1	2	2	1	1	2	3	3	2	1	3	2	1	2	1	3	2	1	1.811	2.06	0.247	−15.25
13	1	2	2	1	2	2	1	2	1	2	1	1	2	3	1	3	2	1	3	3	2	1	2	1.430	0.06	0.228	−15.88
14	1	2	2	1	2	2	1	2	1	2	1	2	3	1	2	1	3	2	1	1	3	2	3	1.679	−0.64	0.264	−16.70
15	1	2	2	1	2	2	1	2	1	2	1	3	1	2	3	2	1	3	2	2	1	3	1	1.311	−2.29	0.214	−18.02
16	1	2	2	2	1	2	2	1	2	1	1	1	2	3	2	1	1	3	2	3	3	2	1	1.574	2.46	0.219	−14.66
17	1	2	2	2	1	2	2	1	2	1	1	2	3	1	3	2	2	1	3	1	1	3	2	1.278	−4.16	0.233	−18.94
18	1	2	2	2	1	2	2	1	2	1	1	3	1	2	1	3	3	2	1	2	2	1	3	1.562	0.03	0.237	−16.34

Table 3 (*Continued*)

No.	Factor																							Production Ship Rate			
	A	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*	*M*	*N*	*O*	*P*	*Q*	*R*	*S*	*T*	*U*	*V*	*W*	β_1	SN_1 (dB)	β_2	SN_2 (dB)
19	2	1	2	2	1	1	2	2	1	2	1	1	2	1	3	3	3	1	2	2	1	2	3	1.379	−1.97	0.199	−18.80
20	2	1	2	2	1	1	2	2	1	2	1	2	3	2	1	1	1	2	3	3	2	3	1	1.486	0.76	0.219	−15.86
21	2	1	2	2	1	1	2	2	1	2	1	3	1	3	2	2	2	3	1	1	3	1	2	1.638	−2.43	0.240	−19.12
22	2	1	2	1	2	2	2	1	1	1	2	1	2	2	3	3	1	2	1	1	3	3	2	1.755	0.54	0.244	−16.59
23	2	1	2	1	2	2	2	1	1	1	2	2	3	3	1	1	2	3	2	2	1	1	3	1.300	−2.67	0.235	−17.53
24	2	1	2	1	2	2	2	1	1	1	2	3	1	1	2	2	3	1	3	3	2	2	1	1.394	−3.47	0.239	−18.79
25	2	1	1	2	2	2	1	2	2	1	1	1	3	2	1	2	3	3	1	3	1	2	2	1.238	−2.15	0.197	−18.09
26	2	1	1	2	2	2	1	2	2	1	1	2	1	3	2	3	1	1	2	1	2	3	3	1.476	−3.00	0.260	−18.08
27	2	1	1	2	2	2	1	2	2	1	1	3	2	1	3	1	2	2	3	2	3	1	1	1.573	−2.75	0.260	−18.39
28	2	2	2	1	1	1	1	2	2	1	2	1	3	2	2	2	1	1	3	2	3	1	3	1.592	−2.36	0.249	−18.48
29	2	2	2	1	1	1	1	2	2	1	2	2	1	3	3	3	2	2	1	3	1	2	1	1.180	−3.04	0.200	−18.46
30	2	2	2	1	1	1	1	2	2	1	2	3	2	1	1	1	3	3	2	1	2	3	2	1.717	0.67	0.258	−15.79
31	2	2	1	2	1	2	1	1	1	2	2	1	3	3	3	2	3	2	2	1	2	1	1	1.618	−1.33	0.233	−18.15
32	2	2	1	2	1	2	1	1	1	2	2	2	1	1	1	3	1	3	3	2	3	2	2	1.752	2.52	0.218	−15.59
33	2	2	1	2	1	2	1	1	1	2	2	3	2	2	2	1	2	1	1	3	1	3	3	1.214	−2.84	0.208	−18.16
34	2	2	1	1	2	1	2	1	2	2	1	1	3	1	2	3	2	3	1	2	2	3	1	1.504	−2.82	0.241	−18.763
35	2	2	1	1	2	1	2	1	2	2	1	2	1	2	3	1	3	1	2	3	3	1	2	1.484	−2.14	0.220	−18.74
36	2	2	1	1	2	1	2	1	2	2	1	3	2	3	1	2	1	2	3	1	1	2	3	1.295	−3.54	0.203	−19.62

baseline process using factor *N*. Factor *T* was used to evaluate the effect of small, medium, and large batch sizes in the tail-end process on-line capacity and stability. Overall workforce staffing level was varied by factor *U*. This was done both to evaluate fabrication line sensitivity and to examine the simulation model sensitivity to workforce variations.

We selected an L_{36} orthogonal array [36] to accommodate the 11 two-level and 10 three-level inner array factors, with column assignments as indicated in Table 2.

4. Experimental Procedure

All simulations and analyses were run using Pentium-class personal computers. Experiment definitions and results were performed using Quattro Pro for Windows 5.0 [4], and the model simulations were created and executed using Taylor II software.

We used a previously developed spreadsheet template with associated macro programs to generate the simulation model control factor combinations according to the L_{36} inner array. Each of these 36 combinations was implemented as a separate model by modifying the baseline (row 1) model.

We imposed the outer array conditions using a Taylor II batch run file to set the signal and noise factor levels at the start of each simulation. The 12 outer array conditions for each level of lot start rate (M_1) were simulated and the results extracted as a group. The results for all 60 outer array runs were stored in five separate files for later analysis.

5. Results

The five data files for each inner array condition were combined into one spreadsheet and the dynamic model sensitivities (β_1 and β_2) and signal-to-noise (SN) ratios (SN_1 and SN_2) were computed using the method presented in Section 7 of the Robust Design Workshop handout [5]. The β's and SN ratios calculated for all of the inner array conditions are shown in Table 3. The data for the conditions with best and worst SN_1 are shown in Figure 3 with the dynamic model lines.

The average factorial effects for each performance parameter were calculated and are shown

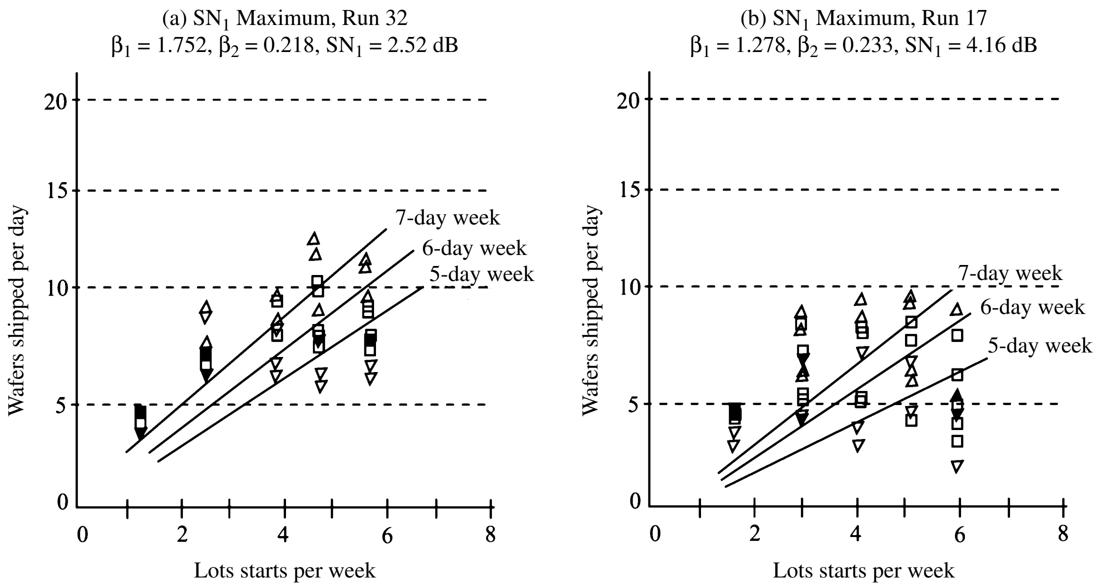

Figure 3
Best- and worst-case inner array conditions

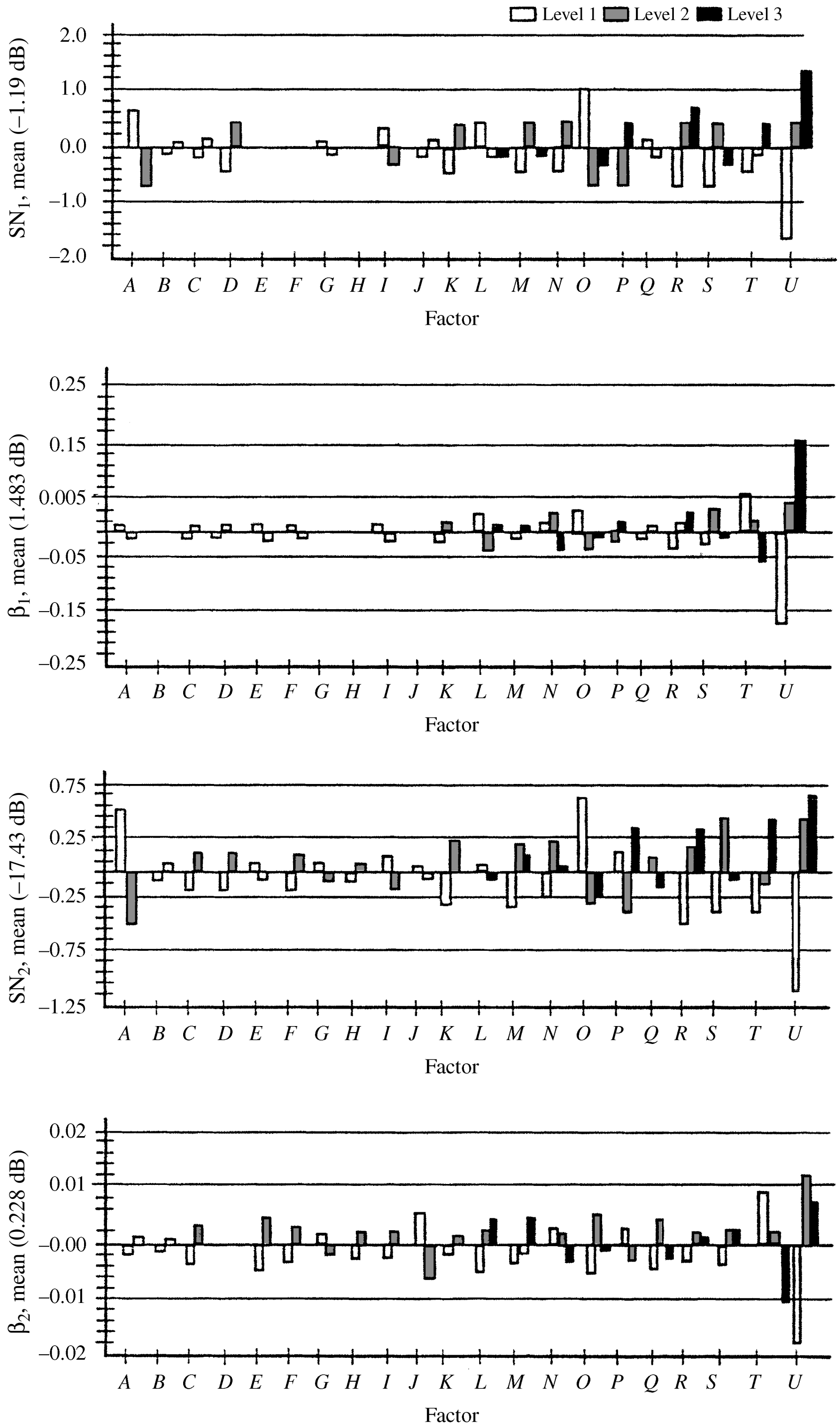

Figure 4
Average factorial effects

Table 4
Summary of inner array response ANOVAs

Factor		Response Parameter[a] (%)				Optimization Decision		
		SN_1	β_1	SN_2	β_2	Choice		Reason
A:	meas	8.4 (1)	—	1.6%	—	A_1:	baseline	SN 1 and 2
B:	spcr1	—	—	—	—	B_1:	baseline	No effect
C:	spcr2	—	—	1.5 (2)	3.7 (2)	C_2:	added	Beta 2
D:	etch1	0.8 (2)	—	1.2 (2)	—	D_2:	added	SN 1 and 2
E:	etch2	1.7 (1)	0.4 (1)	—	5.3 (2)	E_2:	added	Beta 2
F:	snsr1	—	—	—	1.5 (2)	F2:	added	Beta 2
G:	snsr2	—	—	—	—	G_1:	baseline	No effect
H:	PC−cln	—	—	—	—	H_1:	baseline	No effect
I:	D_cln	—	0.7 (1)	—	—	I_1:	baseline	Beta 1
J:	B_cln	—	—	—	2.7 (1)	J_1:	baseline	Beta 2
K:	oven	1.8 (2)	0.8 (2)	3.2 (2)	—	K_2:	added	SN 1 and 2
L:	metal_dep	—	0.6 (1)	—	2.3 (3)	L_3:	c	Beta 2
M:	coater	—	—	—	1.8 (3)	M_3:	3	Beta 2
N:	process	—	1.1 (2)	—	—	N_2:	improved	Beta
O:	stepper	10.5 (1)	1.1 (1)	5.2 (1)	6.3 (2)	O_1:	1	SN 1 and 2
P:	develop	1.7 (3)	0.7 (3)	2.9 (3)	—	P_2:	3	SN 1 and 2
Q:	descum	—	—	—	3.2 (2)	Q_2:	3	Beta 2
R:	screen	4.4 (3)	1.4 (3)	5.9 (3)	—	R_3:	3/2	SN 1 and 2
S:	saw	2.5 (2)	1.3 (2)	3.9 (2)	0.9 (3)	S_2:	2	SN 1 and 2
T:	batch	—	11.2 (1)	3.9 (3)	16.7 (1)	T_1:	s	Beta 1 and 2
U:	staff	38.8 (3)	75.9 (3)	27.6 (3)	39.3 (2)	U_3:	base +2	Scaling factor
Pooled error		29.3	4.9	33.0	16.2			

[a] Numbers in parentheses represent the level that maximizes response.

in Figure 4. An analysis of variance (ANOVA) was performed for each parameter; the results are summarized in Table 4. We used the ANOVA results to identify the influential factors and the factorial effects analysis to choose the levels for the optimum factor combination detailed in Table 4.

We modified the optimum into a second configuration based on fabrication line operational concerns. Factor A (number of verification measurement stations) had been an occasional bottleneck in the past, so we changed to level A_2 ("added"). The largest gain in performance due to factor R (number of screening stations) is between R_1 and R_2; R_3 shows less improvement over R_2. Since R_2 ("2+/1+") demands less equipment and less space, we selected that level. Because the product

Table 5
Confirmation run results summary

	Factor																					Product Ship Rate			
Run	***A***	***B***	***C***	***D***	***E***	***F***	***G***	***H***	***I***	***J***	***K***	***L***	***M***	***N***	***O***	***P***	***Q***	***R***	***S***	***T***	***U***	β_1	SN_1 (dB)	β_2	SN_2 (dB)
37	1	1	2	2	2	2	1	1	1	1	2	3	3	2	1	3	2	3	2	1	3	1.845	3.32	0.267	−14.25
																						1.831	2.29	0.234	−15.57
38	2	1	2	2	2	2	1	1	1	1	2	3	3	3	1	3	2	2	2	1	3	1.788	1.93	0.267	−15.42
																						1.867	2.52	0.240	−15.29

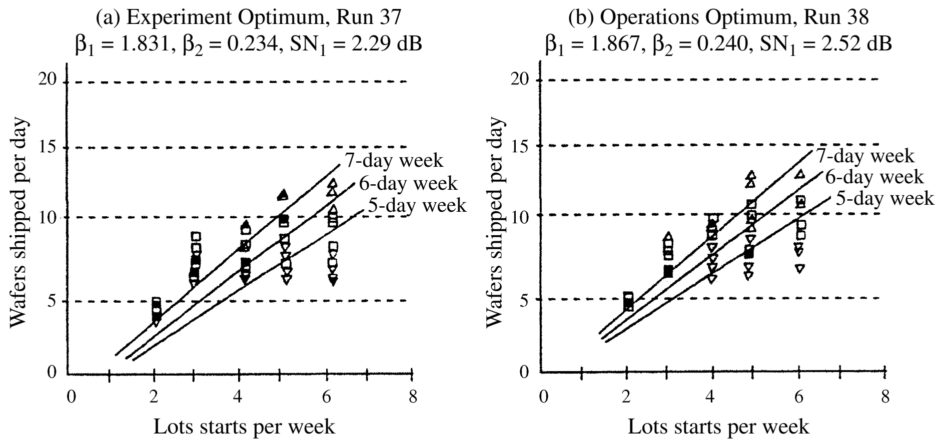

Figure 5
Optimum conditions run results

ship rates spanned by this study were not high enough to meet long-term requirements comfortably, we changed factor M (production process improvement strategies) to M_3 ("improved HD"), which includes provision for a greater number of units per wafer.

The linear predictions and confirmation run results for both the experiment optimum and the modified operations optimum configurations are shown in Table 5, with the factor-level differences shaded. The run data are shown plotted in Figure 5 with the dynamic model lines. Both configurations gave results close to those predicted and with less difference between the two configurations than predicted.

6. Summary and Conclusions

We evaluated the sensitivity of the accelerometer sensor fabrication line expansion to 21 different factors by using an L_{36} orthogonal array to direct the configuration of a validated simulation model. We developed a double-signal dynamic model of the fabrication line ideal function that greatly clarifies the assessment of line capacity and stability. We are now using these results to verify and refine the fabrication line expansion planning and to guide capacity forecasting.

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This case study is contributed by R. K. Ellis.