

**2005 Deliverable Report:
Supply Chain Quadratic Goal Programming Models and Solutions**

**Task 1214.002: Robust Configuration and Monitoring of Semiconductor Supply Chains
Contract 1214: Configuration, Monitoring and Control of Semiconductor Supply Chains**

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1. Abstract and Summary

This report presents a novel approach to formulating and optimizing the semiconductor supply chain performance. Unlike conventional modeling of supply chain operations, empirical quadratic models are established to describe the supply chain behavior. Quadratic goal programming model is then used to optimize the supply chain performance. In order to construct the quadratic response-surface models of supply chain performance, a supply chain simulation model is first set up. Simulation runs are then conducted based on a D-optimum experimental design. By the results of simulation experiments, quadratic models for different QoS priorities are built with stepwise regression. The quadratic response surfaces then serve as the objective functions of the goal programming model. Optimization is finally performed to obtain a robust supply chain configuration with its X-factors and cycle-time variability minimized.

2. Technical Results

2.1 Semiconductor Supply Chain Simulation

In this study, a four-tier semiconductor supply chain is simulated. The first tier is Fabrication (Fab); the second is Circuit Prob. (CP); the third is Assembly (Ass); and the fourth is Final Test (FT). There are six fabrication facilities and their corresponding capacities are designed to mimic 200mm foundry fabs of renowned companies, such as TSMC, and UMC (Table 1). Each of the CP, the ASS and the FT tier has two facilities available to the supply chain. There are nine available supply chain routes (Fig. 1) to serve three products, A, B and C. However, not all the available routes are usable to each type of the products (Table 2). Since the supply chain simulation model is an aggregated model, the most challenging task is to estimate the cycle time of a facility, especially of the fabrication facility, which usually consists of more than 300 processing steps. The cycle time can be divided into two portions: processing time and queue time. The processing times vary with the product type and the facility. The queue times are assumed to follow log-normal distributions with means varying with the capacity utilization and the QoS priority. Finally, the mean of the log-normal distribution is determined such that the mean cycle time appears to be an exponential function of the capacity utilization (Fig. 2). The simulation model is built using EM Plant .

2.2 Quadratic Response Surface Models

There are two types of input variables and two types of response variables for the supply chain response surface models. The input variables are also the decision variables for the goal programming. The first type of input variables is the route mix variable, ρ_{kr} . Route mix ρ_{kr} represents the proportion of product k ($k=1$ for Product A, 2 for Product B and 3 for Product C) demand to be allocated to supply chain route r . The second type of input variables is the priority mix variable, π_{kq} . Priority mix π_{kq} denotes the proportion of product k demand to be produced in QoS priority level q . In this study, there are three QoS priority levels: super hot lots ($q=1$), hot lots ($q=2$) and normal lots ($q=3$). The two types of response variables are to be used to evaluate the entire supply chain's performance. The first type of variables is to measure the X-factor performance for each priority level. The second type of response variables is to measure the cycle time variability, i.e. cycle time standard deviation (CT-STD) in month. 180 runs of simulations chosen by D-optimum design are performed to obtain how the response variables are affected by the input variables. Stepwise regression is then used to select input variable terms, including linear, quadratic and interaction terms, into the response surface model. The resulting response surface models for QoS priority 1 are shown below.

$$\begin{aligned} \mathbf{X-factor}_1 = & 3.04028 - 0.76932 * \rho_{18} - 5.32407 * \pi_{11} * \rho_{18} - \\ & 1.70306 * \rho_{22} + 2.55627 * \pi_{11} * \rho_{22} - \\ & 3.21206 * \rho_{24} + 2.0617 * \pi_{11} * \rho_{24} + 3.35593 * \rho_{22} * \\ & \rho_{24} + 6.45807 * \rho_{24}^2 - \\ & 6.01907 * \rho_{26} + 2.64128 * \pi_{11} * \rho_{26} + 2.43013 * \rho_{18} * \\ & \rho_{26} + 3.95107 * \rho_{22} * \rho_{26} + \\ & 3.59718 * \rho_{24} * \rho_{26} + 6.27775 * \rho_{26}^2 - 2.08025 * \rho_{24} * \\ & \rho_{33} + 0.95507 * \rho_{33}^2 - \\ & 0.89682 * \rho_{22} * \pi_{12} - 2.73278 * \rho_{22} * \pi_{21} - 2.94563 * \\ & \rho_{24} * \pi_{21} + 4.33951 * \pi_{11} * \pi_{31} \\ & + 2.20954 * \rho_{22} * \pi_{31} + 2.26427 * \rho_{26} * \pi_{31} - \\ & 3.90953 * \rho_{33} * \pi_{31} + 3.88601 * \pi_{11} * \pi_{32} - \\ & 0.69994 * \rho_{33} * \pi_{32} - 3.96577 * \pi_{11} * \rho_{11} - 1.57582 * \\ & \rho_{22} * \rho_{14} - 1.4345 * \rho_{15} - \\ & 6.01892 * \pi_{11} * \rho_{15} + 4.19858 * \rho_{26} * \rho_{15} + 6.76398 * \\ & \pi_{21} * \rho_{15} \end{aligned}$$

$$\begin{aligned} \mathbf{CT-STD}_1 = & 10.76424 - 30.39664 * \rho_{18} + 20.91593 * \rho_{17} * \rho_{18} + \\ & 44.38031 * \rho_{18}^2 - 7.04376 * \rho_{22} + \end{aligned}$$

$$\begin{aligned}
& 3.75327 * \pi_{11} * \rho_{22} - 19.49143 * \rho_{17} * \rho_{22} - \\
& 14.41669 * \rho_{24} - 19.90259 * \rho_{17} * \rho_{24} + \\
& 17.13541 * \rho_{22} * \rho_{24} + 19.52764 * \rho_{24}^2 - 16.44176 * \\
& \rho_{26} - 20.93092 * \rho_{17} * \rho_{26} + \\
& 15.80926 * \rho_{22} * \rho_{26} + 16.97536 * \rho_{24} * \rho_{26} + \\
& 23.21307 * \rho_{26}^2 + 5.01638 * \rho_{22} * \pi_{22} - \\
& 6.09423 * \pi_{31} + 9.03262 * \rho_{22} * \pi_{31} + 9.70458 * \rho_{24} * \\
& \pi_{31} + 7.29345 * \pi_{12} * \pi_{31} - \\
& 16.26179 * \rho_{11} + 18.03107 * \rho_{17} * \rho_{11} + 27.58228 * \rho_{18} * \\
& \rho_{11} - 5.73555 * \pi_{12} * \rho_{11} + 28.52365 * \rho_{17} * \rho_{14} \\
& + 29.47225 * \rho_{18} * \rho_{14} - 5.43344 * \rho_{22} * \rho_{14} + \\
& 23.20821 * \rho_{11} * \rho_{14} - 55.31215 * \rho_{14}^2 - 17.66627 * \rho_{15} \\
& + 17.71866 * \rho_{17} * \rho_{15} + 22.28432 * \rho_{18} * \rho_{15} + \\
& 11.24435 * \rho_{26} * \rho_{15} - 5.38951 * \pi_{22} * \rho_{15} + \\
& 32.58414 * \rho_{11} * \rho_{15} + 25.65426 * \rho_{14} * \rho_{15}
\end{aligned}$$

2.3 Quadratic Goal Programming Models

With the quadratic response surfaces to describe how the supply chain performance responds to changes of supply chain configurations, the response surfaces can be used as the goal functions in the goal programming. The goal objective function is then:

$$\sum_{i=1}^3 w_i (X\text{-factor}_i + CT\text{-STD}_i)$$

where w_i is the weight for priority i products; $X\text{-factor}_i$ is the X-factor response surface for priority i and $CT\text{-STD}_i$ is the CT-STD response surface for priority i . The constraints are listed below.

1. Product mix constraint:

$$\sum_k p_k = 1$$

where p_k is the proportion of product k demand in the total demand and is given.

2. Priority mix constraints:

$$\sum_k p_k \cdot \pi_{kq} \leq \phi_q \quad \forall q$$

$$\sum_q \pi_{kq} = 1 \quad \forall k$$

where ϕ_q is a preset upper limit for priority q proportion.

3. Route mix constraints:

$$\sum_k p_k \cdot \rho_{rk} \leq \alpha_r \quad \forall r$$

$$\sum_r \rho_{rk} = 1 \quad \forall k$$

where α_r is a preset upper limit for the proportion of total demand to go through route r .

4. Capacity constraints:

$$E_t \cdot \sum_{r:\phi \in r} \sum_k (p_k \cdot \rho_{rk}) \cdot \frac{PT_{kt\phi}}{PT_{t\phi}} \leq C_{t\phi} \quad \forall t, \phi$$

where

E_t is capacity utilization of supply chain tier t (an economy factor);

$C_{t\phi}$ is proportion of facility f capacity in supply chain tier t ;

$PT_{t\phi}$ is average bottleneck operation processing time by facility f in supply chain tier t ; and

$PT_{kt\phi}$ is average bottleneck operation processing time of product k by facility f in supply chain tier t .

2.4 Supply Chain Optimization and Validation

With the quadratic goal programming model, optimization is performed using LINDO. Since the quadratic goal programming model has only linear constraints, the optimum solution found is ensured to be the global optimum. The results are shown in Table 3. The optimum supply chain route mix and priority mix settings are then validated through simulation and compared to the 180 simulation experiments in Table 4.

Table 1: Fab Capacity in Simulation Model

FAB	Capacity	
FAB1	1468k	<ul style="list-style-type: none"> ● Capacity in 200mm wafers per year ● Fab1:TSMC 5, 6, or 8 ● Fab2:UMC 8C, 8D, 8E, or 8F ● Fab3:TSMC 2 ● Fab4:TSMC 3, 4, or 7 ● Fab5:UMC 6A, or 8AB ● Fab6:WaferTech ,VIS , or SSMC
FAB2	1376k	
FAB3	922k	
FAB4	1133k	
FAB5	1202k	
FAB6	689k	
Total	6465 k	

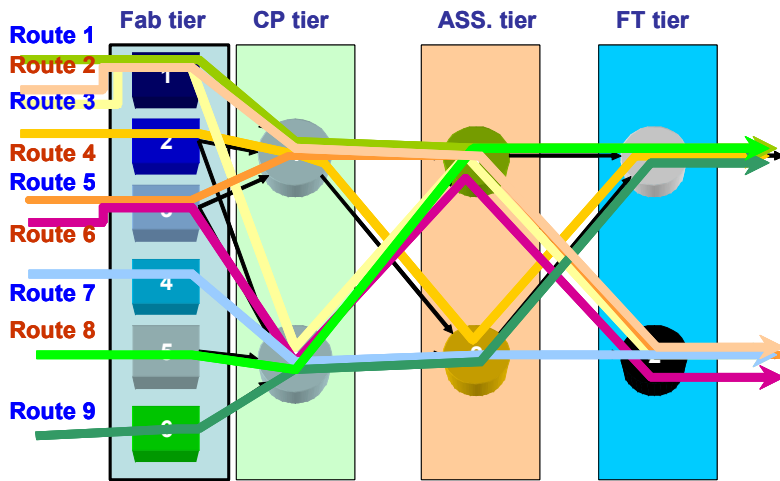


Fig. 1 Semiconductor Supply Chain Routes

Table 2: Usable Routes for Products

Product	Routes
A	1 4 5 7 8 9
B	2 4 6 7
C	3 4

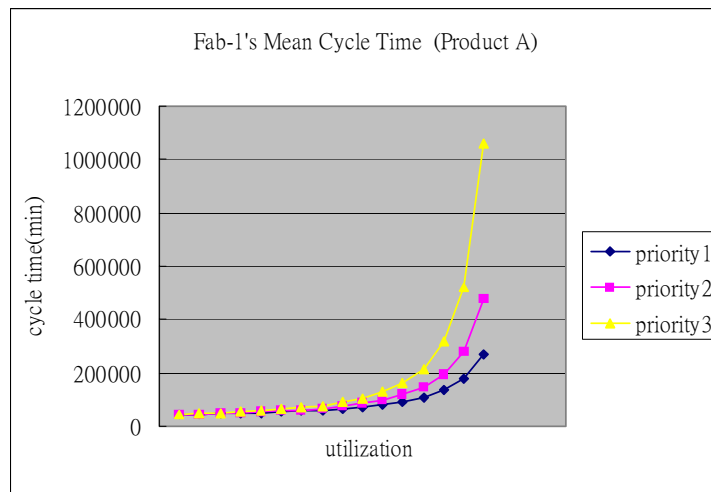


Fig. 2 Mean Cycle Time vs. Capacity Utilization

Table 3 Optimum Supply Chain Configuration

Priority Mix	Product 1	Product 2	Product 3
Priority 1	0.05	0.05	0.15
Priority 2	0.1	0.25	0.25
Priority 3	0.85	0.7	0.6

Route Mix	Route 1	Route 4	Route 5	Route 7	Route 8	Route 9
Product 1	0.2	0.1	0.114994	0.147153	0.183181	0.254671
Route Mix	Route 2	Route 4	Route 6	Route 7		
Product 2	0.1	0.235856	0.3	0.364144		
Route Mix	Route 3	Route 4				
Product 3	0.529286	0.470714				

Table 4: Validation of Optimized Supply Chain Performance

X factor		Priority1	Priority2	Priority3
180 Runs of Simulation Experiments	MIN	1.40331	1.47294	1.703227
	AVG	1.5897	1.8307	2.12257
	MAX	2.19528	2.19381	2.338799
Goal Programming Results		1.396099	1.566981	2.128181
Simulation Validation of Goal Programming		1.3957	1.632579	2.078058
CT-STD (month)		Priority1	Priority2	Priority3
180 Runs of Simulation Experiments	MIN	0.48536	0.81575	1.24547
	AVG	1.09511	1.43061	1.8152
	MAX	3.53199	2.48982	2.60458
Goal Programming Results		0.3891889	0.2292796	1.4254032
Simulation Validation of Goal Programming		0.486637	0.748724	1.20554