Research ID 879
Demand Data Mining and Planning in Semiconductor Manufacturing Networks

National Taiwan University

Argon Chen
Yon-Chun Chou
Shi-Chung Chang
Ruey-Shan Guo
# 879 Task Summary

<table>
<thead>
<tr>
<th>Number</th>
<th>Task/Activity</th>
<th>Task Leader</th>
<th>Deliverable(s)</th>
<th>Students</th>
<th>Liaisons</th>
</tr>
</thead>
<tbody>
<tr>
<td>879</td>
<td>Demand Data Mining and Planning in Semiconductor Manufacturing Networks</td>
<td>Argon Chen</td>
<td>Final Report (12/03)</td>
<td>Ron Billings, ISMT</td>
<td>F. Robertson, Intel M. Janakarim, Intel</td>
</tr>
</tbody>
</table>
## 879 Task Liaisons

<table>
<thead>
<tr>
<th>Core</th>
<th>Liaisons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stanley, K.J.</td>
<td>Tony Yu, UMC</td>
</tr>
<tr>
<td>Bonal, Javier</td>
<td>Kenny Chien, UMC</td>
</tr>
<tr>
<td>Cervantes, Ed</td>
<td>Ying Tat Leung, IBM</td>
</tr>
<tr>
<td>Farey, Lawrence</td>
<td>Sarah Hood, IBM</td>
</tr>
<tr>
<td>Hood, Sarah</td>
<td>Jonathan Wang, IBM</td>
</tr>
<tr>
<td>Robertson, Frank</td>
<td>Jonathan Hosking, IBM</td>
</tr>
<tr>
<td>Schomig, Alexander</td>
<td>Jonathan Chang, TSMC</td>
</tr>
<tr>
<td></td>
<td>Ajay Sevak, Intel</td>
</tr>
<tr>
<td></td>
<td>Michael O'Brien, Intel</td>
</tr>
<tr>
<td></td>
<td>Christina Chen, Motorola</td>
</tr>
<tr>
<td></td>
<td>Kishore Potti, TI</td>
</tr>
<tr>
<td></td>
<td>Pratap Javangula, TI</td>
</tr>
</tbody>
</table>

---

**SRC/ISMT Factory Operations Research Center – Project 879 Proprietary**

3
879 Project Management

• Project Website
  – http://www.ie.ntu.edu.tw/Dr_Chen/SRC.htm

• Weekly site meetings at NTU
• Weekly task meetings for Tasks 1 and 2

• Quarterly Teleconferences with all industrial liaisons and PI’s
• On-site visits to member companies once a year
• Meetings with and visits to Suppliers upon requests
879 Executive Summary

Based on inputs from industrial liaison and core team members, we continue our original research work on the demand/capacity planning problems. We continue to produce new ideas on demand disaggregation and forecasting problems and novel analysis framework and risk model for capacity planning problems. The results can be summarized as follows:

– We have developed dynamic EWMA and double-EWMA demand disaggregation methodologies. The methodologies have been tested using both simulated DRAM demand data and actual semiconductor demand data. Results show great improvement over the conventional methods (task 1)

– We have investigated the fundamental issues of demand aggregation, forecasting and disaggregation. The results show that methods of demand forecasting along with disaggregation, though a very common practice, should be employed with great caution (task 1, presented in INFORMS 2002)

– We have developed a framework of analysis for capacity planning under uncertain product demands (task 2)

– We have developed a method to optimize the risk of capacity plans (task2)
879.001: Intelligent Demand Aggregation and Forecast Solutions

Research Personnel:

- Task Leader: Argon Chen
- Faculty:
  - Ruey-Shan Guo
  - Shi-Chung Chang
- Students
  - Peggy Lin, NTU, MS 6/02
  - Yi-Chung Chang, NTU, MS 6/02
  - Ken Chen, NTU, MS 6/02
  - Chun-Hung Lan, NTU, MS 6/02
  - Hung-Shuo Hsia, NTU, MS 6/02
  - Bo-Wei Hsieh, NTU, PhD 6/02
  - Ji-Chyuan Liou, NTU, PhD
  - Tony Huang, NTU, MS 6/03
  - Kyle Yang, NTU, MS 6/03
879.001: Intelligent Demand Aggregation and Forecast Solutions

Primary Anticipated Results:

• Fundamental research on demand planning
  – Issues of aggregating, forecasting and disaggregating interrelated demands

• Useful demand planning strategies and methodologies
  – Demand planning hierarchy: the optimum demand aggregation/disaggregation structure
  – Forecasting by proportional disaggregation: accurate estimate of product mix of a product family

• A prototype of demand planning software system that incorporated our proposed strategies and methodologies.
879.001: Intelligent Demand Aggregation and Forecast Solutions

Task Description:

- **Year 1** – Conduct fundamental study on the effects of demand grouping and develop demand grouping strategies. A multivariate time series model is used as the study vehicle to investigate the effects of aggregating interrelated demands. Demand grouping strategies are then proposed to optimize inventory and capacity plans. Define a demand planning structure (DPS) for top-down, middle-out or bottom-up demand planning.

- **Year 2** - Develop an optimal DPS and forecasting methodologies for aggregated and disaggregated demands. Fundamental research will be first conducted to investigate the effects of aggregating, forecasting and disaggregating interrelated demands. Forecasting strategies are then proposed within the optimal demand planning structure.

- **Year 3** – Develop an integrated demand data mining and planning software prototype. Statistical properties, natures, and interrelations of demands will be automatically mined out by the software. Optimal aggregation and statistical forecasting strategies will be then suggested to the demand planners.
879.001: Intelligent Demand Aggregation and Forecast Solutions

Task Deliverables:

• Intelligent multidimensional demand aggregation/disaggregation strategies (Model, Report) (Year 1) ⇒ Demand Planning Hierarchy

• Forecasting methodologies for multidimensional aggregated demands (Model, Report) (Year 2) ⇒ Forecasting by Proportional Disaggregation

• Integrated demand aggregation/forecast prototype system (Software, Report) (Year 3)
879.001: Intelligent Demand Aggregation and Forecast Solutions

• Executive Summary:

  – We have developed dynamic EWMA and double-EWMA demand disaggregation methodologies. The methodologies have been tested using both simulated DRAM demand data and actual semiconductor demand data. Results show great improvement over the conventional methods.

  – We have investigated the fundamental issues of demand aggregation, forecasting and disaggregation. The results show that methods of demand forecasting along with disaggregation, though a very common practice, should be employed with great caution.

  – We are in the process of applying for patents for “Demand Planning Hierarchy” and “Dynamic EWMA Demand Disaggregation Methods”.

  – Currently, i2 Technologies, Adex and a local data mining company have shown great interest in technology transfer of both.

  – We will develop a prototype of “Demand Planning Hierarchy” software system and test it with more cases of actual semiconductor demand data.
Outlines

1. Conventional Disaggregation Methods
3. EWMA Disaggregation Methods
4. Dynamic Disaggregation Method
5. Dynamic Disaggregation Method with PLC Indicator
6. Simulated Demand Model
7. Double EWMA Disaggregation Method
8. Performance Comparison
Problem Description

1. Aggregating demand for better forecast
   - How to disaggregate?

2. Effect of Product Life Cycle
   - How to Consider PLC Effect in disaggregation?

Total Forecast

- P(1)=?
- P(2)=?
- P(3)…..
- P(n)=?

USA → Africa

Europe → 

Asia → ......

Stage:
- Introduction
- Growth
- Maturity
- Decline
Conventional Disaggregation Method

- **Method-A**
  
  \[ P_{i,n+1} = \frac{\sum_{t=1}^{n} P_{i,t}}{n} \]
  
  (Average the Proportion of previous “n” periods to estimate the proportion next time period)

- **Method-B**
  
  \[ P_{i,n+1} = \frac{\sum_{t=1}^{n} d_{i,t}}{\sum_{t=1}^{n} D_t} \]
  
  (Average the demand of previous “n” periods to estimate the proportion next time period)
Proposed Methodology - EWMA

- Exponentially Weighted Moving Average statistic is introduced to catch the PLC

\[ w_t = \alpha (1 - \alpha)^{n-t} \]

- Exponential weights

\[ \alpha : \text{Exponential weight parameter} \]
\[ t : \text{Exponential weight for time period "t"} \]
\[ n : \text{Number of total historical data} \]

- Different products have different \( \alpha \) values for best SSE performance.

(Demand is stable) \( \alpha = 0.1 \)  
(Demand is changing) \( \alpha = 0.5 \)
EWMA Disaggregation Formula

\[
\hat{P}_{i,n+1} = \frac{\sum_{t=1}^{n} w_{i,t} \cdot d_{i,t}}{\sum_{j=1}^{m} \sum_{t=1}^{n} w_{j,t} \cdot d_{j,t}}
\]

and

\[
\sum_{t=1}^{n} w_{i,t} = \sum_{t=1}^{n} \frac{\alpha_i (1 - \alpha_i)^{n-t}}{1 - (1 - \alpha_i)^n} = 1
\]

- \(d_{i,k}\) = Demand of product “i” at time “k”
- \(w_{i,k}\) = Weight of product “i” at time “k”
- \(n\) = Number of total historical data
- \(m\) = Number of total products
- \(\alpha_i\) = Smoothing constant of product “i”

Apply EWMA weights to historical “demand”
Sum of all EWMA weighted demands
Exponential weights

### EWMA Disaggregation Formula

<table>
<thead>
<tr>
<th>Product</th>
<th>Time</th>
<th>Week 1</th>
<th>Week 2</th>
<th>Week 3</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(w_A(\alpha_A=0.1))</td>
<td>0.3690</td>
<td>0.3321</td>
<td>0.2989</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>(w_B(\alpha_B=0.5))</td>
<td>0.5714</td>
<td>0.2857</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demand A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0</td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Demand B</td>
<td></td>
<td>0.2857</td>
<td>0.3321</td>
<td>0.3690</td>
<td></td>
</tr>
</tbody>
</table>

**Weights**

\[
W_A(\alpha_A=0.5) = \frac{2}{3} \quad \text{and} \quad W_B(\alpha_B=0.1) = \frac{1}{3}
\]

**Demands**

\[
\text{Demand A} = 140 \quad \text{and} \quad \text{Demand B} = 60
\]

**EWMA**

\[
\text{EWMA}(\alpha_A) = \frac{1}{3} \quad \text{and} \quad \text{EWMA}(\alpha_B) = \frac{1}{3}
\]

\[
\frac{19.299}{67.869} = 0.284 \quad \text{and} \quad \frac{48.57}{67.869} = 0.716
\]
Determine the “$\alpha$”

by minimizing the proportion estimating error of the last “k” periods

$$SSE = \sum_{t=n-k}^{n} \sum_{j=1}^{m} (Squared \ Error)_{j,t} = \sum_{t=n-k}^{n} \sum_{j=1}^{m} (\hat{P}_{i,t} - P_{i,t})^2$$

$P_{i,t}$ : Proportion of product “$i$” at time “$t$”

$\hat{P}_{i,t}$ : EWMA estimated proportion of product “$i$” at time “$t$”

Squared Error $i = (\hat{P}_{i,n-2} - P_{i,n-2})^2 + (\hat{P}_{i,n-1} - P_{i,n-1})^2 + (\hat{P}_{i,n} - P_{i,n})^2 = SSE$

Example of $k=3$

Minimize the squared error of the last “k” periods to find the best “$\alpha$”

Use the “$\alpha$” estimate the proportion next time period
Steepest Descent Method

Ineffective and time consuming
Different products have different \( \alpha \) values for best SSE performance.

- \( \alpha \) is expected to be higher at "Growth" or "Decline" phase of PLC
- \( \alpha \) is expected to be lower at "Maturity" phase of PLC

\( \alpha = 0.1 \) weight (Demand is stable)
\( \alpha = 0.5 \) weight (Demand is changing)

Different products have different \( \alpha \) values for best SSE performance.
PLC Indicator – Sample Auto-Correlation

\[ SAC = \frac{Sample \ Autocovariance}{Sample \ Variance} \]

- SAC is the correlation between the former and later datasets of the same data
- \( \uparrow \) when the data trend is significant
- \( \downarrow \) when data is without a trend (stable)
1. Use the indicator - “SAC” to estimate the $\alpha$ dynamically.
2. The PLC effect is considered and the disaggregation accuracy is improved.
3. Computation time of searching suitable $\alpha$ is greatly reduced.

- Given the Initial $\alpha_i$ by Steepest-Descent Search
- Calculate SAC$_t$
- New data available
- Calculate new SAC$_{t+1}$ and SAC trend (SAC$_{t+1}$-SAC$_t$)
- Use the SAC trend to estimate the new $\alpha$ at the next period

END

START
Characteristics of Industrial Demands

1. Effect of PLC

2. “Standard deviation of demand is proportional to demand mean” (D. C. Heat & P. L. Jackson), (R. G. Brown)

Product demand at different time period can be seen as different distributions with specific mean and standard deviation that is proportional to its mean.

3. Product Substitution within the product family
The Simulated DRAM Demand Dataset

- 3 products, 150-week demand data
- Product-1 is simulated as 256MB
- Product-2 is simulated as 128MB
- Product-3 is simulated as 512MB
- Each phase is simulated about 50 week length (1 year)
Different sample size of SAC is used to estimate the $\alpha$ and the PLC phase transition.

Sample size “15” (1/4 phase), “25” (1/2 phase) and “50” (1 phase) is tested.

The SAC does reflect the expected $\alpha$ trend and the PLC phase transition.
Performance Comparisons

Performance metric: Proportion Mean Squared Error

\[
PMSE = \frac{1}{100} \sum_{t=50+1}^{50+100} \sum_{i=1}^{3} (\hat{P}_{i,t} - P_{i,t})^2
\]

\(P_{i,t}\) : Proportion of product “i” at time “t”
\(\hat{P}_{i,t}\) : Estimated proportion of product “i” at time “t”

Testing Data: Simulated Demand Data

Testing Methods:
1. Conventional Method-A
2. Conventional Method-B
3. PIDE-SAC method: PIDE method indicated by SAC.
   (SAC sample size 15, 25, 50 are tested as PIDE-SAC-15, PIDE-SAC-25, PIDE-SAC-50 methods)

Testing Results:

<table>
<thead>
<tr>
<th>Method</th>
<th>Total PMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Conventional Method</strong></td>
<td></td>
</tr>
<tr>
<td>Method-A</td>
<td>0.072740</td>
</tr>
<tr>
<td>Method-B</td>
<td>0.064664</td>
</tr>
<tr>
<td><strong>PIDE Method (SAC)</strong></td>
<td></td>
</tr>
<tr>
<td>PIDE-SAC-15</td>
<td>0.004540</td>
</tr>
<tr>
<td>PIDE-SAC-25</td>
<td>0.001962</td>
</tr>
<tr>
<td>PIDE-SAC-50</td>
<td>0.002375</td>
</tr>
</tbody>
</table>

● “25(1/2 PLC phase)” is examined the relative suitable sample size for SAC
Limitation of EWMA Method

Consider a “n-period” proportion data

- The EWMA statistic is not able to capture the future trend beyond the historical data range.

The EWMA statistic is not able to capture the future trend beyond the historical data range.

The Double EWMA smoothing constant $\beta$ is introduced to estimate the “future trend”
PLC Indicator Dynamic Double EWMA (PIDDE) Method

\[ \hat{P}_{i,n+1} = \hat{M}_{i,n+1} + \Delta \hat{P}_{i,n+1} \]

\[ \hat{M}_{i,n+1} = \frac{\sum_{t=1}^{n} w_{i,t} \cdot d_{i,t}}{\sum_{j=1}^{m} \sum_{t=1}^{n} w_{j,t} \cdot d_{j,t}} \]

\[ \Delta \hat{P}_{i,n+1} = \frac{\left( \sum_{t=1}^{n} v_{i,t} \cdot \Delta d_{i,t} \right) - \hat{M}_{i,n} \left( \sum_{j=1}^{m} \sum_{t=1}^{n} v_{j,t} \cdot \Delta d_{j,t} \right)}{D_n + \sum_{j=1}^{m} \sum_{t=1}^{n} v_{j,t} \cdot \Delta d_{j,t}} \]

\[ \sum_{i=1}^{n} v_{i,t} = \frac{\sum_{i=1}^{n} \beta_i (1 - \beta_i)^{n-t}}{1 - (1 - \beta_i)^n} = 1 \]

\[ \sum_{i=1}^{n} w_{i,t} = \frac{\sum_{i=1}^{n} \alpha_i (1 - \alpha_i)^{n-t}}{1 - (1 - \alpha_i)^n} = 1 \]

\[ \hat{P}_{i,k} \] = Proportion estimates of product “i” at time “k”

\[ \hat{M}_{i,k} \] = Proportion’s mean estimates of product “i” at time “k”

\[ \Delta \hat{P}_{i,k} \] = Proportion difference estimates of product “i” at time “k”

\[ d_{i,k} \] = Demand of product “i” at time “k”

\[ \Delta d_{i,k} = d_{i,k} - d_{i,k-1} \] = Demand difference of product “i” at time “k” and “k-1”

\[ \alpha_i, \beta_i \] = Smoothing Constant of product “i”

n = Number of total historical data

m = Number of total products
**Indicator of $\beta$ – Sample Auto-Correlation**

$$\hat{\Delta P}_{i,n+1} = \frac{\left(\sum_{t=1}^{n} v_{i,t} \cdot \Delta d_{i,t}\right) - \hat{M}_{i,n} \left(\sum_{j=1}^{m} \sum_{t=1}^{n} v_{j,t} \cdot \Delta d_{j,t}\right)}{D_n + \sum_{j=1}^{m} \sum_{t=1}^{n} v_{j,t} \cdot \Delta d_{j,t}}$$

$$\sum_{t=1}^{n} v_{i,t} = \sum_{i=1}^{n} \frac{\beta_i (1 - \beta_i)^{n - t}}{1 - (1 - \beta_i)^n} = 1$$

Since $\Delta P_i$ is estimated by $\beta$, SAC of proportion differences “$\Delta P_i$” is used as the indicator for $\beta$ determination.

$\beta$ is expected to be higher when the slope of demand trend changes (as $\Delta P_i$ SAC).
Performance Comparison

**Testing Methods**: (sample sizes: 15, 25, and 50)
Conventional Methods A and B
SDDE: Steepest Descent Dynamic EWMA
SDDDE: Steepest Descent Dynamic Double EWMA
PIDE: PLC Indicator Dynamic EWMA
PIDDE: PLC Indicator Dynamic Double EWMA

**Testing Results**:

<table>
<thead>
<tr>
<th></th>
<th>Conventional Method</th>
<th>SDDE Method</th>
<th>SDDDE Method</th>
<th>PIDE Method</th>
<th>PIDDE Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total PMSE</td>
<td>Computation Time</td>
<td>Total PMSE</td>
<td>Computation Time</td>
<td>Total PMSE</td>
</tr>
<tr>
<td>Method-A</td>
<td>0.072740</td>
<td>&lt; 1 sec</td>
<td>SDDE-15</td>
<td>0.000943</td>
<td>20 minutes</td>
</tr>
<tr>
<td>Method-B</td>
<td>0.064664</td>
<td>&lt; 1 sec</td>
<td>SDDE-25</td>
<td>0.000888</td>
<td>40 minutes</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>SDDE-50</td>
<td>0.001037</td>
<td>90 minutes</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>PIDDE-SAC-15</td>
<td>0.001036</td>
<td>25 minutes</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>PIDDE-SAC-25</td>
<td>0.001109</td>
<td>75 minutes</td>
</tr>
</tbody>
</table>
Actual Semiconductor Demand

Graph showing the demand over time for different products:
- RP-1 Demand
- RP-2 Demand
- RP-3 Demand
Appendix – Real Data Proportion

![Graphs showing the proportion of data over time for RP-1, RP-2, and RP-3 proportions.](image)
Performance Comparison

Testing Data: Simulated Demand Data and Real Semiconductor Demand Data: 3 products, 121 weeks (60→historical data, 61→forecast)

Testing Results:

<table>
<thead>
<tr>
<th>Conventional Method</th>
<th>Total PMSE</th>
<th>Computation Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method-A</td>
<td>0.009766</td>
<td>&lt; 1 sec</td>
</tr>
<tr>
<td>Method-B</td>
<td>0.011467</td>
<td>&lt; 1 sec</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>PIDE Method</th>
<th>Total PMSE</th>
<th>Computation Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>PIDE-SAC-15</td>
<td>0.008208</td>
<td>1 minutes</td>
</tr>
<tr>
<td>PIDE-SAC-25</td>
<td>0.007813</td>
<td>2 minutes</td>
</tr>
<tr>
<td>PIDE-SAC-50</td>
<td>0.007875</td>
<td>4 minutes</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>PIDDE Method</th>
<th>Total PMSE</th>
<th>Computation Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>PIDDE-SAC-15</td>
<td>0.008335</td>
<td>7 minutes</td>
</tr>
<tr>
<td>PIDDE-SAC-25</td>
<td>0.008137</td>
<td>25 minutes</td>
</tr>
<tr>
<td>PIDDE-SAC-50</td>
<td>0.010753</td>
<td>43 minutes</td>
</tr>
</tbody>
</table>
Findings

- EWMA and double EWAM disaggregation formulas are developed.

- “Sample Autocorrelation” is found in this research to be a good indicator of PLC phase transition.

- The proposed PLC indicator dynamic disaggregation methods effectively improve the disaggregation accuracy by considering PLC effects.

- The best-performed sample size is about ½ of one PLC phase.

- Double EWMA method is more effective for short PLC products and EWMA method is suitable for long PLC products.