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

National Taiwan University

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879 Task Summary

Number	***Task/Activity***	***Task Leader***	***Deliverable(s)***	***Students***	***Liasons***
879	Demand Data Mining and Planning in Semiconductor Manufacturing Netwroks	Argon Chen	Final Report (12/03)		Ron Billings, ISMT F. Robertson, Intel M. Janakarim, Intel
879.001	Intelligent Demand Aggregation and Forecast Solutions	Argon Chen	Annual Report 12/01 Annual Report 12/02 Annual Report 12/03	Peggy Lin Yi-Chung Chang Ken Chen Chun-Hung Lan Hung-Shuo Hsia Bo-Wei Hsieh Ji-Chyuan Liou Tony Huang Kyle Yang	Tony Yu, UMC Kenny Chien, UMC Ying Tat Leung, IBM Sarah Hood, IBM Jonathan Wang, IBM Jonathan Hosking, IBM Jonathan Chang, TAMC Ajay Sevak, Intel Michael O'Brien, Intel Christina Chen, Motorola Kishore Potti, TI Pratap Javangula, TI
879.002	Integration of Demand Planning and Manufacturing Planning	Yon-Chun Chou	Annual Report 12/01 Annual Report 12/02 Annual Report 12/03	Jin-Zhong Lin Jolin Yang Yi-Yu Liang Yu Heng Chang	

879 Task Liaisons

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Kenny Chien, UMC
Ying Tat Leung, IBM
Sarah Hood, IBM
Jonathan Wang, IBM
Jonathan Hosking, IBM
Jonathan Chang, TSMC
Ajay Sevak, Intel
Michael O'Brien, Intel
Christina Chen, Motorola
Kishore Potti, TI
Pratap Javangula, TI

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
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  - Bo-Wei Hsieh, NTU, PhD 6/02
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  - 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

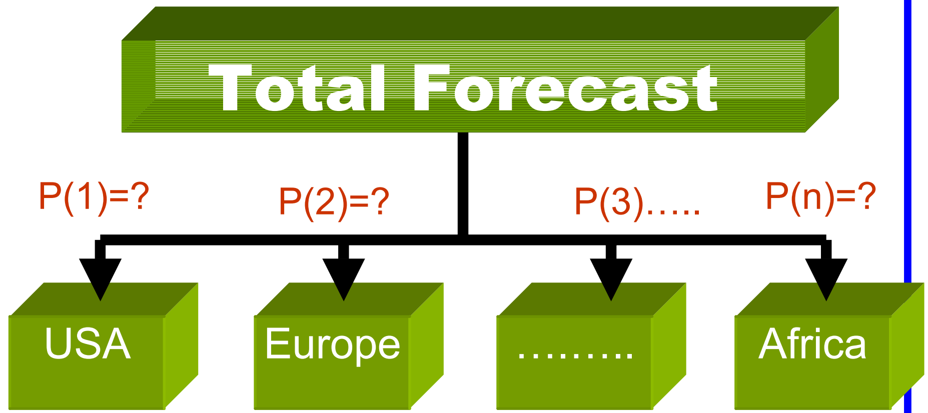
1. Conventional Disaggregation Methods
3. EWMA Disaggregation Methods
4. Dynamic Disaggregation Method
5. Dynamic Disaggregation Method with PLC Indicator
6. Simulated Demand Model
7. Double EWMA Disaggregation Method
8. Performance Comparison

Problem Description

Aggregating demand for better forecast

1

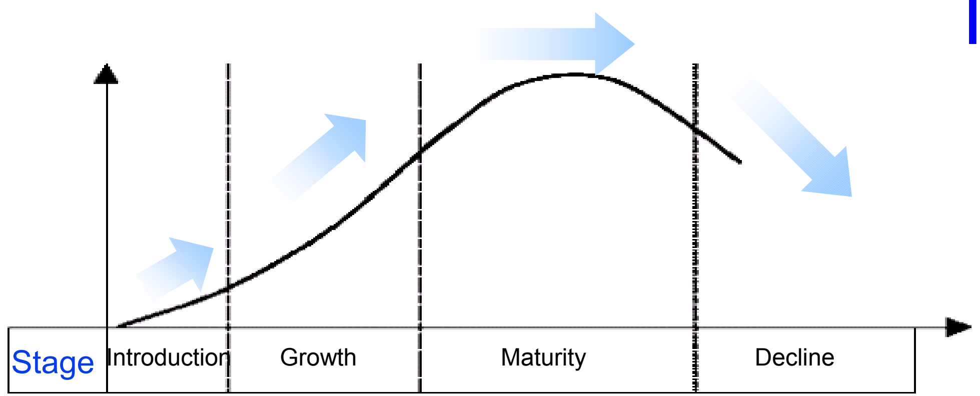
Disaggregating for detailed planning
How to disaggregate?



Effect of Product Life Cycle

2

How to Consider PLC Effect in disaggregation?



Conventional Disaggregation Method

Method-A

$$P_{i,n+1} = \sum_{t=1}^{n} P_{i,t} \Big/ n$$

(Average the Proportion of previous "n" periods to estimate the proportion next time period)

Product \ Time	Week 1	Week 2	Week 3	
A	10	20	30	
B	40	80	20	
Total	50	100	50	Method-A
Proportion A	0.2	0.2	0.6	0.333
Proportion B	0.8	0.8	0.4	0.667

Method-B

$$P_{i,n+1} = \frac{\sum_{t=1}^{n} d_{i,t}}{n} \Bigg/ \frac{\sum_{t=1}^{n} D_{t}}{n}$$

(Average the demand of previous "n" periods to estimate the proportion next time period)

Product \ Time	Week 1	Week 2	Week 3	Total	Method-B
A	10	20	30	60	0.300
B	40	80	20	140	0.700
Total	50	100	50	200	

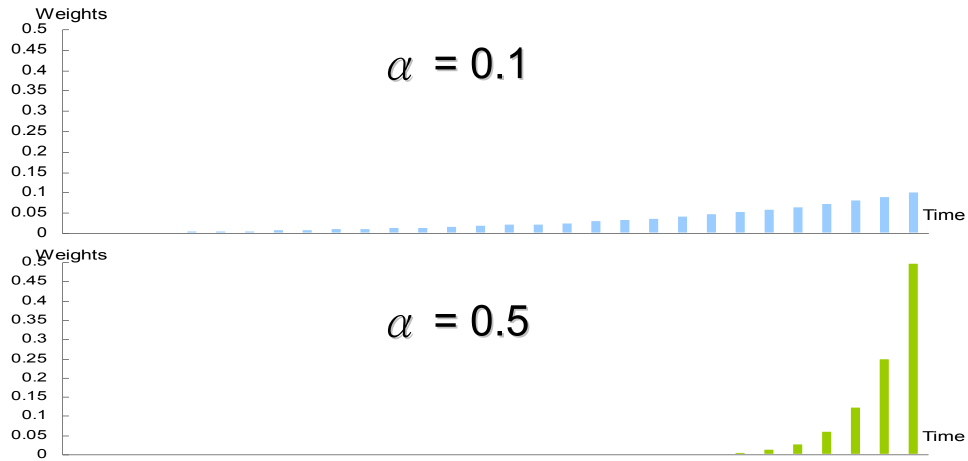
Proposed Methodology - EWMA

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

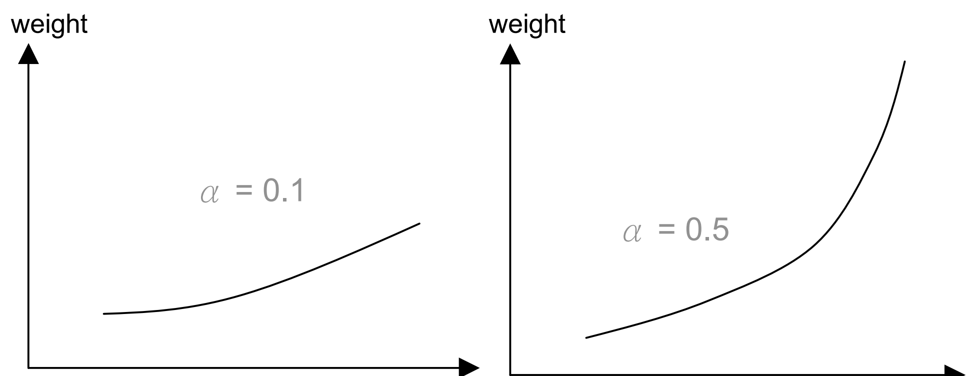
- Exponential weights

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

α : Exponential weight parameter
t : Exponential weight for time period “t”
n : Number of total historical data



- Different products have different “α” values for best SSE performance.



(Demand is stable) (Demand is changing)

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

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

Apply EWMA weights to historical “demand”

Sum of all EWMA weighted demands

Exponential weights

Product \ Time	Week 1	Week 2	Week 3	Total	
w_A(α_A=0.1)	0.3690	0.3321	0.2989	1	
W_B(α_B=0.5)	0.5714	0.2857	0.1429	1	
Demand A	10	20	30	60	
Demand B	40	80	20	140	EWMA
A x α_A	3.690	6.642	8.967	19.299	19.299 / 67.869 = 0.284
B x α_B	22.856	22.856	2.858	48.57	48.57 / 67.869 = 0.716

Weights

Demands

$w_{1,t} \cdot d_{1,t}$

α_A=0.5

$w_{2,t} \cdot d_{2,t}$

α_B=0.1

$d_{i,k}$ = 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
α_i = Smoothing constant of product “i”

Determine the “ α ”

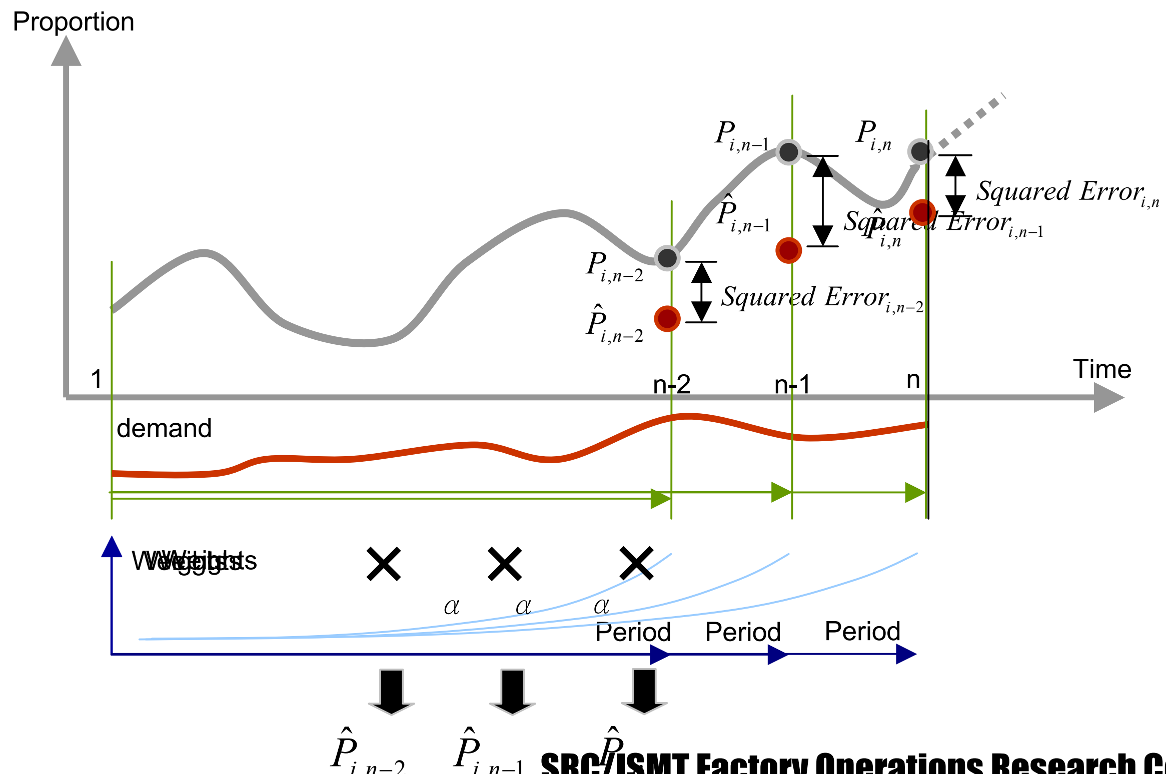
by minimizing the proportion estimating error of the last “k” periods

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

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

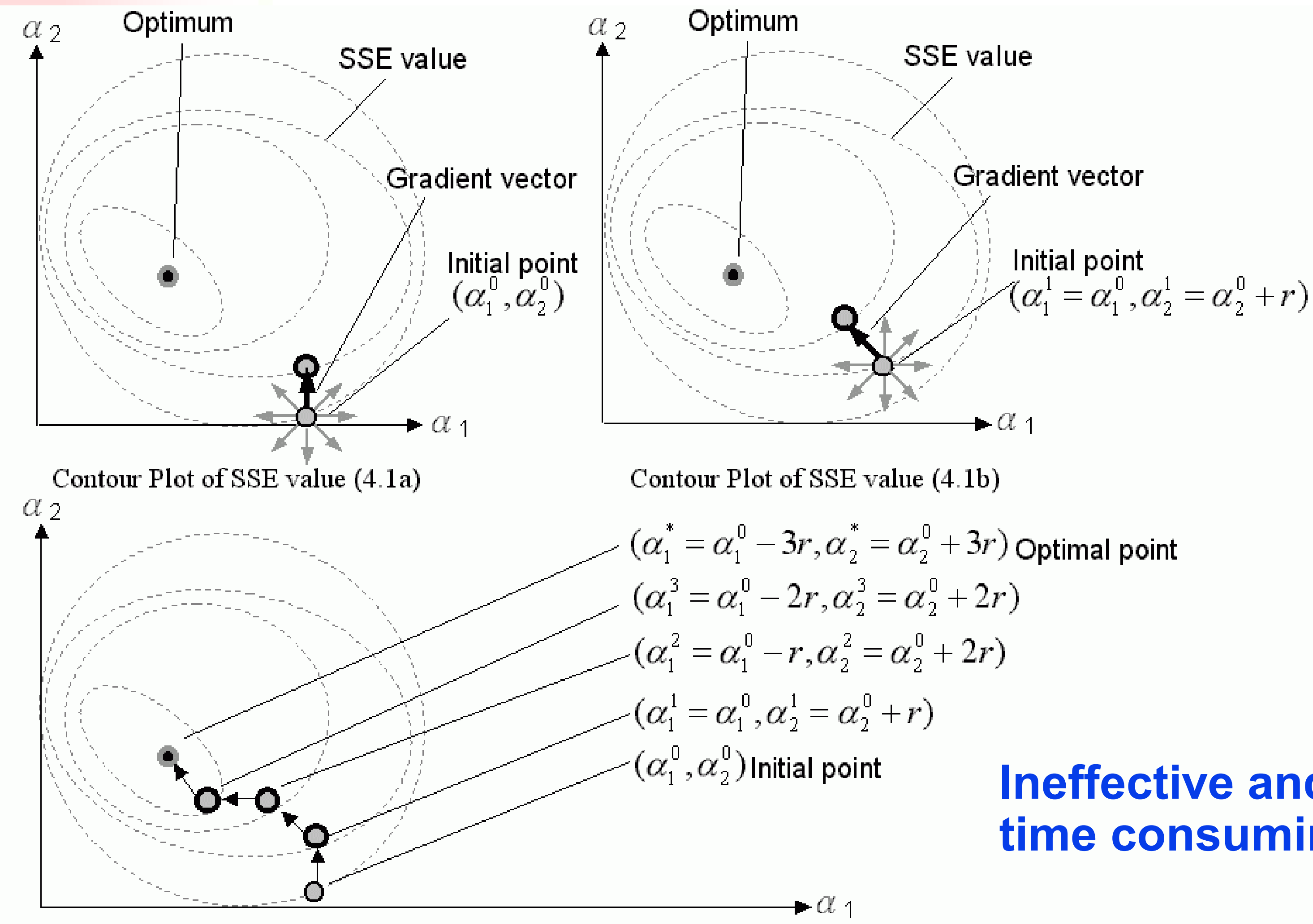
$\hat{P}_{i,t}$:EWMA estimated proportion of product “j” at time “t”

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



- Example of k=3
- Minimize the squared error of the last “k” periods to find the best “ α ”
- Use the “ α ” estimate the proportion next time period

Steepest Descent Method



Contour Plot of SSE value (4.1a)

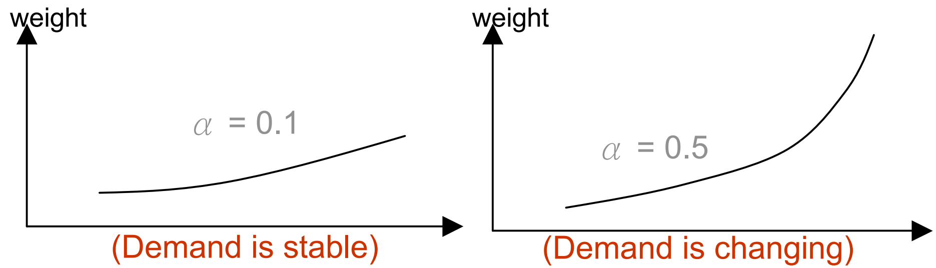
Contour Plot of SSE value (4.1b)

Contour Plot of SSE value (4.1c)

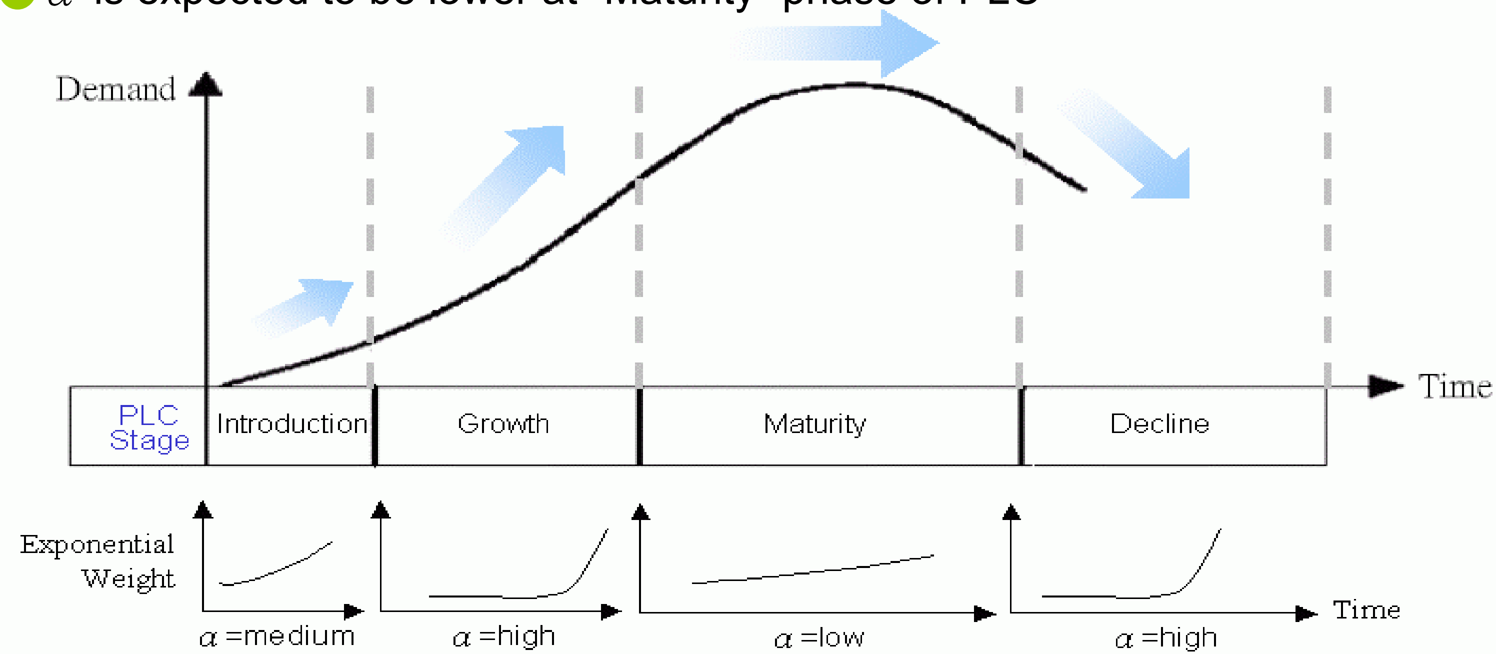
Ineffective and time consuming

"α" and PLC

- Different products have different "α" values for best SSE performance.



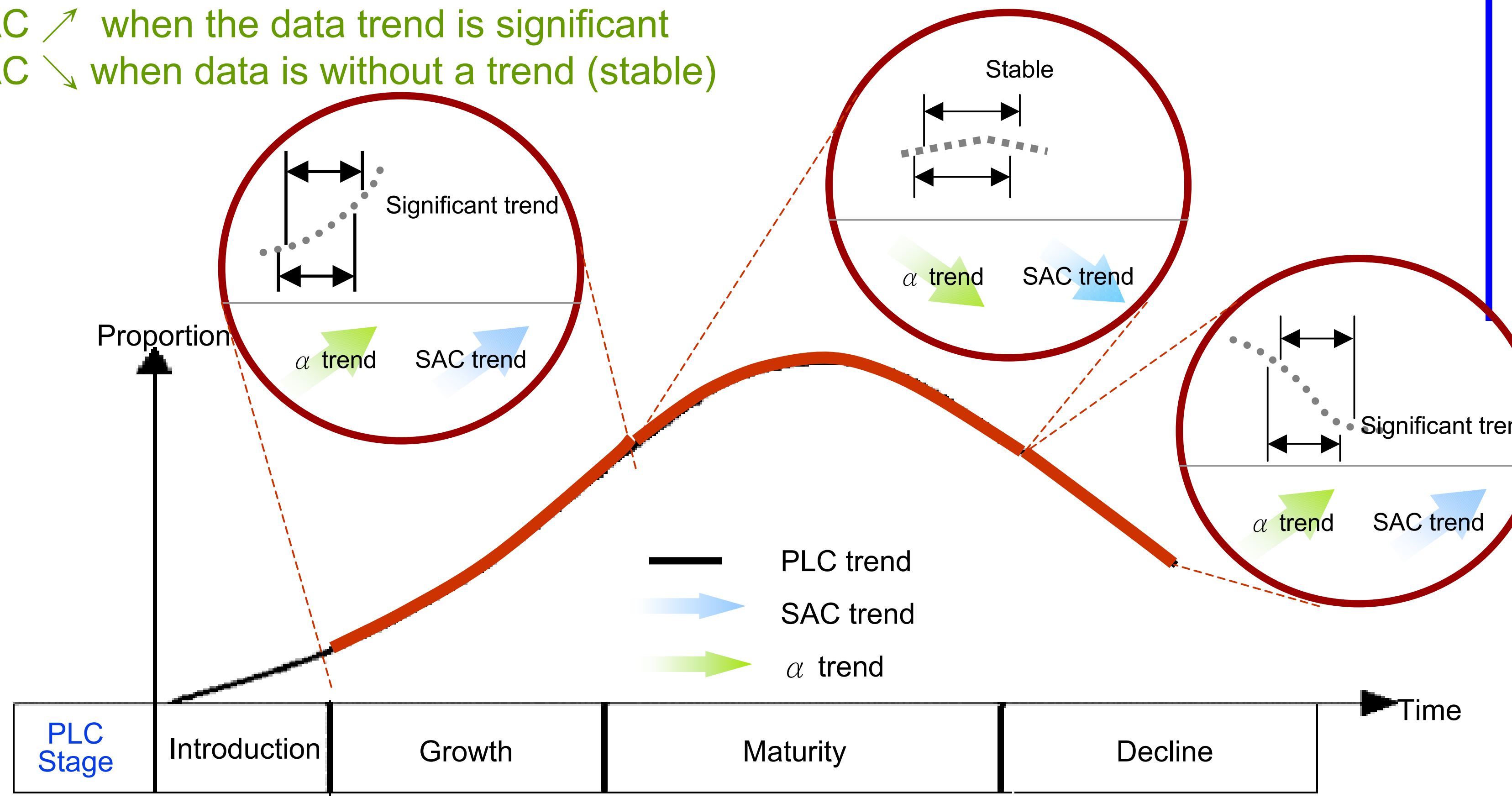
- α is expected to be higher at "Growth" or "Decline" phase of PLC
- α is expected to be lower at "Maturity" phase of PLC



PLC Indicator – Sample Auto-Correlation

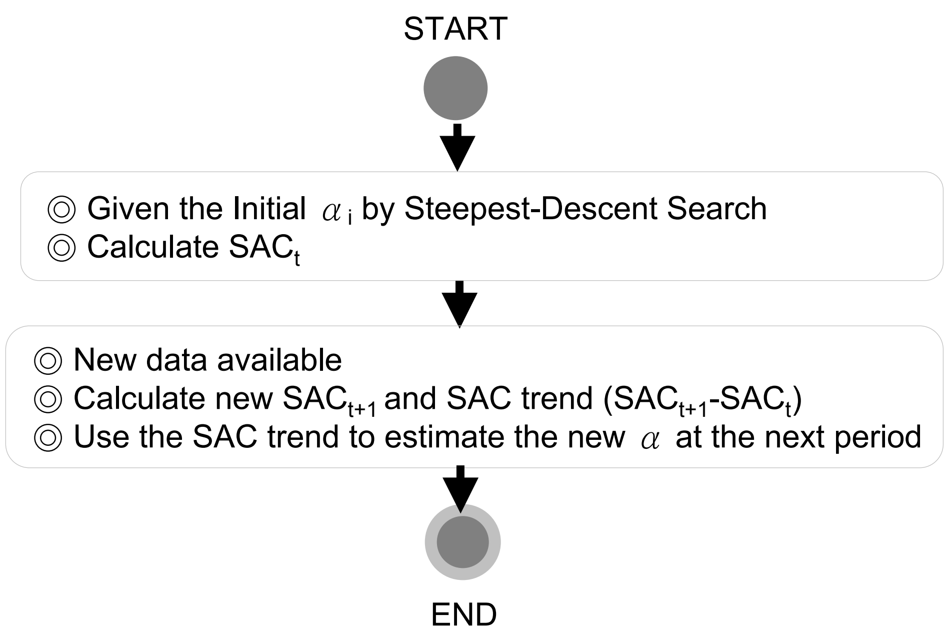
$$SAC = \frac{Sample\ Autocovariance}{Sample\ Variance}$$

- SAC is the correlation between the former and later datasets of the same data
- SAC ↗ when the data trend is significant
- SAC ↘ when data is without a trend (stable)



PLC Indicator Dynamic EWMA (PIDE) Method

1. Use the indicator - “SAC” to estimate the α dynamically.
2. The PLC effect is considered and the disaggregation accuracy is improved.
3. Computation time of searching suitable α is greatly reduced.

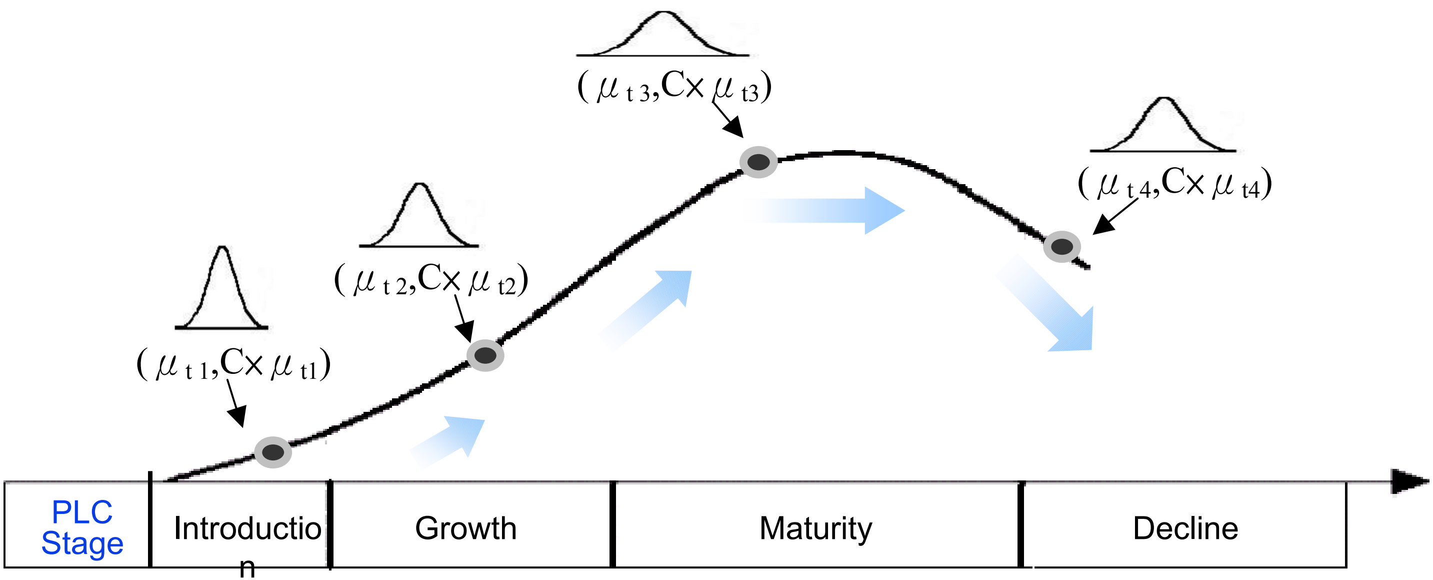


Characteristics of Industrial Demands

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

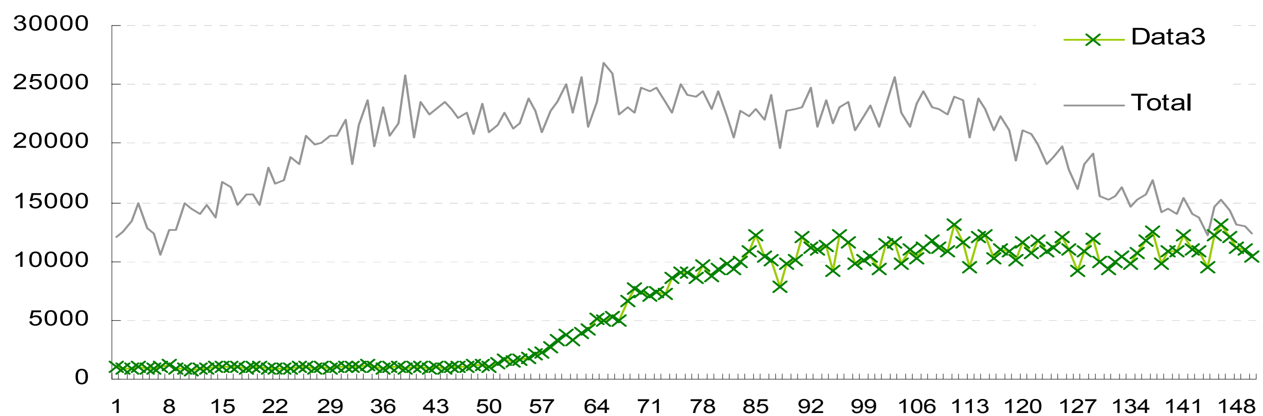


3. Product Substitution within the product family

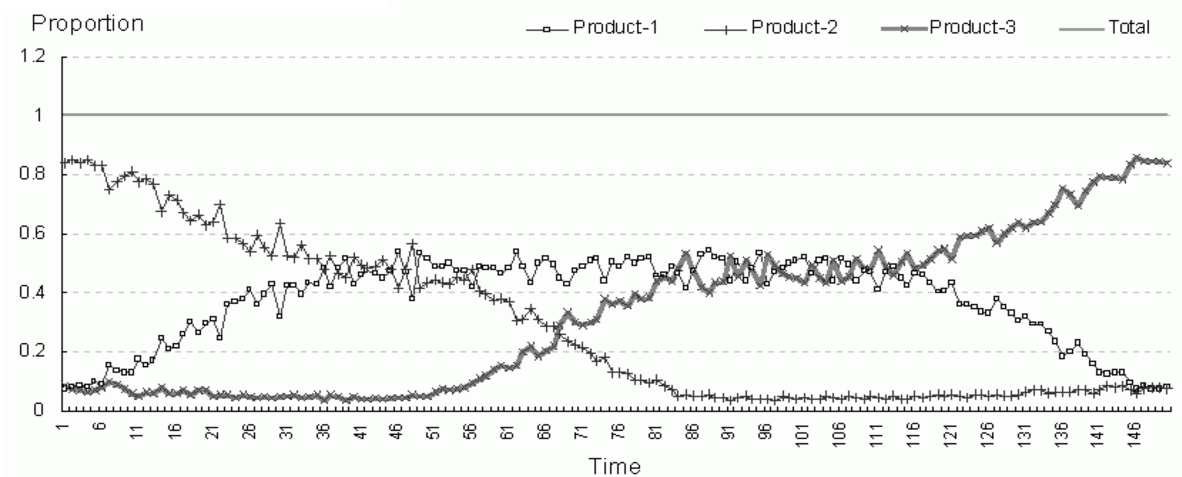
The Simulated DRAM Demand Dataset

- 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)

Simulated demand

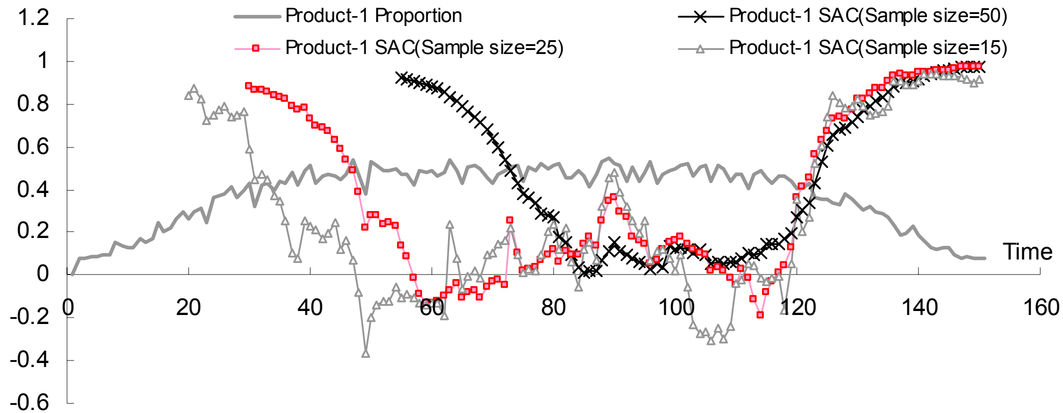


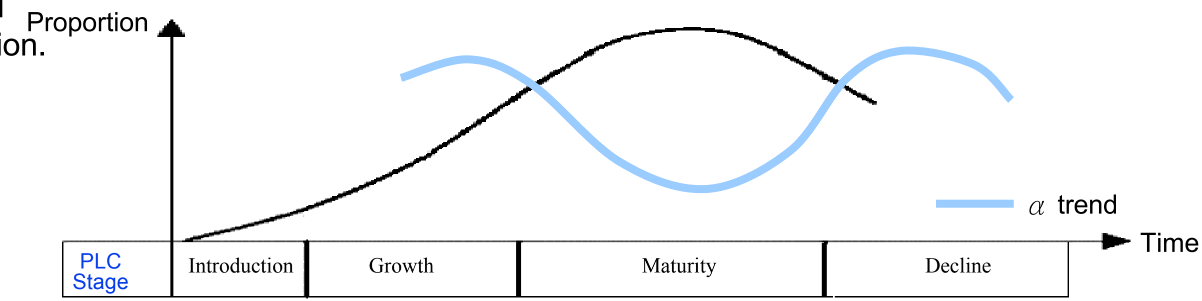
Resulting Proportion



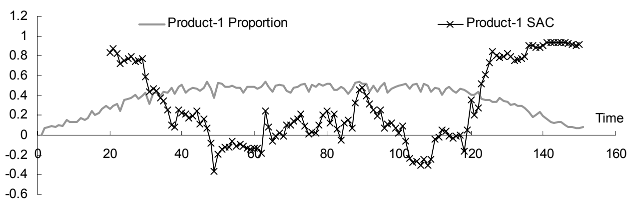
SAC of Simulated Dataset

- Different sample size of SAC is used to estimate the α 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 α trend and the PLC phase transition.

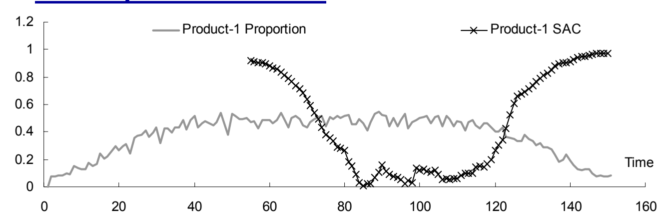




Sample size 15



Sample size 50



Performance Comparisons

Performance metric: Proportion Mean Squared Error

$$PMSE = \sum_{t=50+1}^{50+100} \sum_{i=1}^{3} (\hat{P}_{i,t} - P_{i,t})^2 \Big/ 100$$

$P_{i,t}$: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)

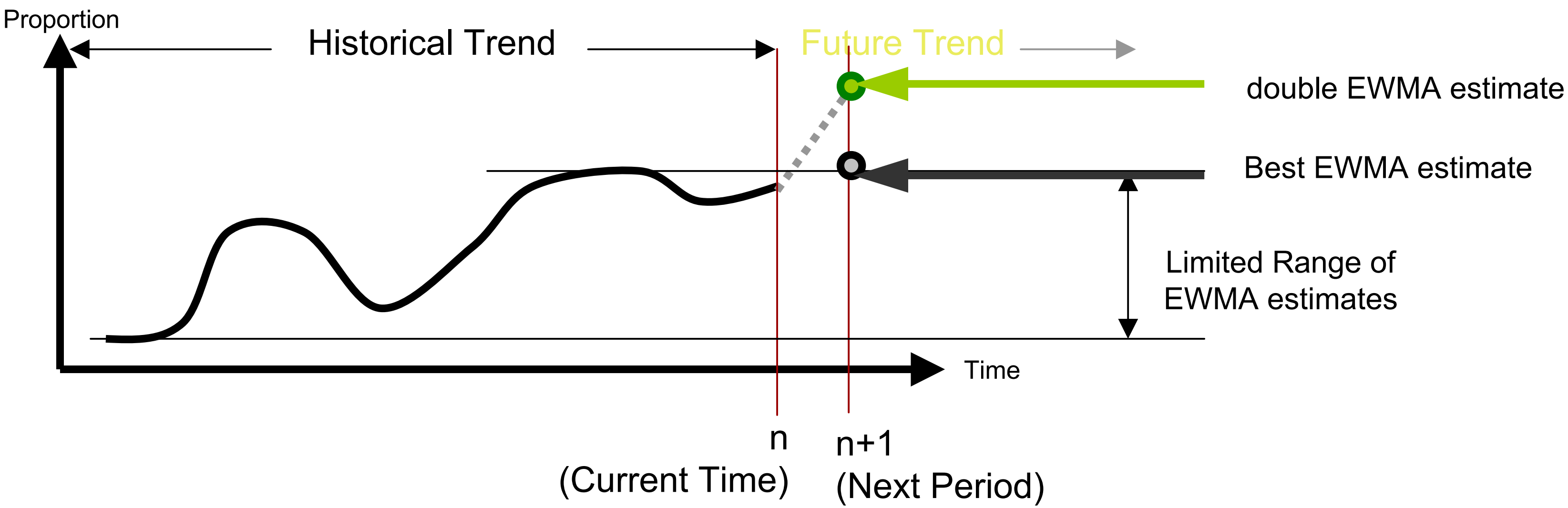
Testing Results :

Conventional Method	*Total PMSE*
Method-A	0.072740
Method-B	0.064664
PIDE Method (SAC)	*Total PMSE*
PIDE-SAC-15	0.004540
PIDE-SAC-25	0.001962
PIDE-SAC-50	0.002375

● "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 Double EWMA smoothing constant β is introduced to estimate the "future trend"

PLC Indicator Dynamic Double EWMA (PIDDE) Method

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

Estimate the proportion Mean level ($\sum M=1$)

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

Estimate the proportion increase ($\sum \Delta P=0$)

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

Exponential weights

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

$M_{i,k}$ = 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”

α_i , β_i = Smoothing Constant of product “i”

n = Number of total historical data

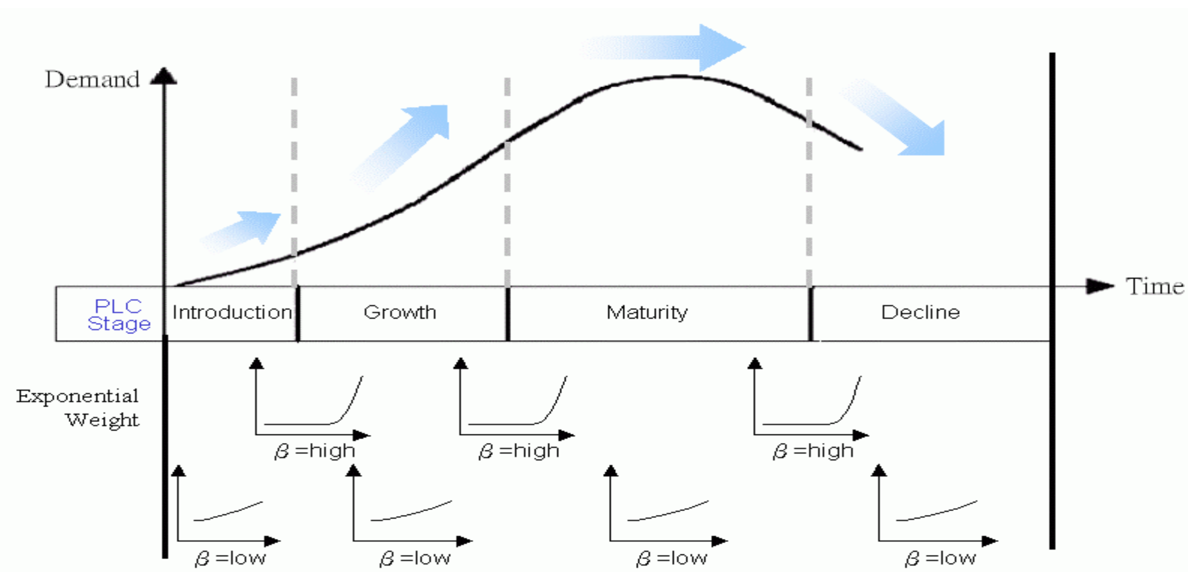
m = Number of total products

Indicator of β – Sample Auto-Correlation

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

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

Since ΔP_i is estimated by β, SAC of proportion differences "ΔP_i" is used as the indicator for β determination



- β is expected to be higher when the slope of demand trend changes (as ΔPi SAC)

Performance Comparison

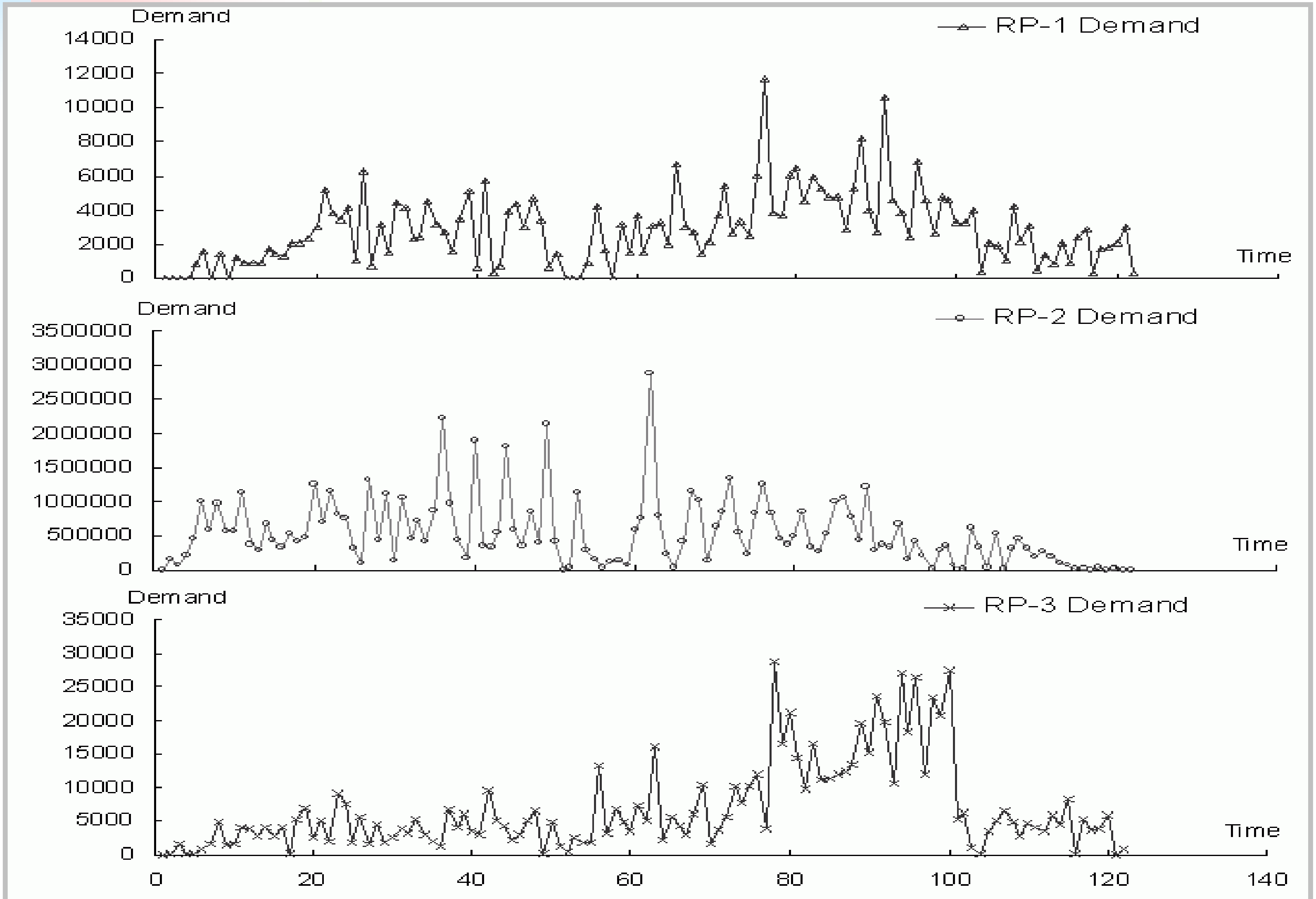
Testing Methods : (sample sizes: 15, 25, and 50)

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

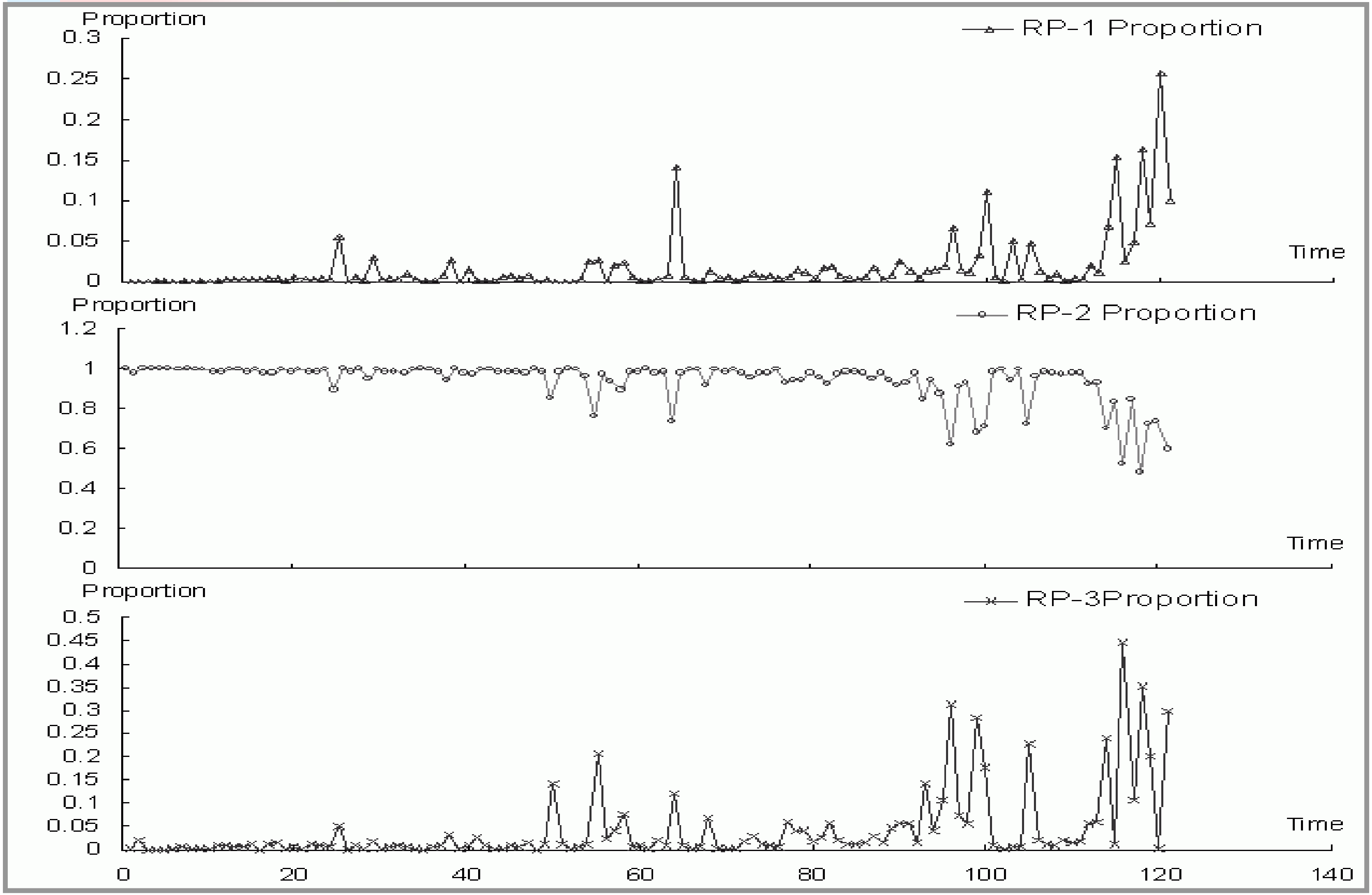
Testing Results :

Conventional Method	*Total PMSE*	*Computation Time*
Method-A	0.072740	< 1 sec
Method-B	0.064664	< 1 sec
SDDE Method	*Total PMSE*	*Computation Time*
SDDE-15	0.000943	20 minutes
SDDE-25	0.000888	40 minutes
SDDE-50	0.001037	90 minutes
SDDDE Method	*Total PMSE*	*Computation Time*
SDDDE-15	0.000942	20 hours
SDDDE-25	0.000872	35 hours
SDDDE-50	0.001025	72 hours
PIDE Method	*Total PMSE*	*Computation Time*
PIDE-SAC-15	0.004540	1 minutes
PIDE-SAC-25	0.001962	2 minutes
PIDE-SAC-50	0.002375	4 minutes
PIDDE Method	*Total PMSE*	*Computation Time*
PIDDE-SAC-15	0.001036	25 minutes
PIDDE-SAC-25	0.001017	43 minutes
PIDDE-SAC-50	0.001109	75 minutes

Actual Semiconductor Demand



Appendix – Real Data Proportion



Performance Comparison

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

Testing Results :

Conventional Method	*Total PMSE*	*Computation Time*
Method-A	0.009766	< 1 sec
Method-B	0.011467	< 1 sec
PIDE Method	*Total PMSE*	*Computation Time*
PIDE-SAC-15	0.008208	1 minutes
PIDE-SAC-25	0.007813	2 minutes
PIDE-SAC-50	0.007875	4 minutes
PIDDE Method	*Total PMSE*	*Computation Time*
PIDDE-SAC-15	0.008335	7 minutes
PIDDE-SAC-25	0.008137	25 minutes
PIDDE-SAC-50	0.010753	43 minutes

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.