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Exploit the value of production data to discover opportunities for saving power consumption by production tools

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Abstract –This study has demonstrated how to apply datamining technics, Neural Networks (NNs), to estimate the power consumption (kilowatt hour per move, kwh/move) of individual process tool sets in a semiconductor factory, and to analyze the relationships between kwh/move and 19 individual input factors, which included "lot size", "process time", "uptime", "usable machine", "Q-time constrain", "sampling rate" and etc.. An empirical study was conducted by using the equipment data of a real fab. The results showed that the proposed approaches can discover rich opportunities, 17.37%, for saving power consumption by production tools.

Index: big data, data mining, semicounductor, power saving

INTRODUCTION

The semiconductor manufacturing industry is not only a technology-intensive but also an energy-intensive industry. For a semiconductor wafer fab, the facility system accounts for 56% of the total power consumption[1,2]. Consequently, most of previous works focus on suppression of power consumption by the facility system. Little research has been done to save power consumption by process tools that account for 41% of power consumed in the fab.

This study aims to fill the gap by establishing neural networks (NNs) to exploit the value of the wealthy production data and equipment data to discover opportunities for saving power consumption by production tools.

METHODOLOGY

A. Data Mining

Data mining has been applied in various fields, in which NNs form the backbone of many data mining techniques [3]. Data mining problems are generally categorized as four types of tasks: 1) regression; 2) classification; 3) clustering; and 4) association [4]. Data mining has been employed as manufacturing intelligence approach to extract useful information and derived patterns from manufacturing data to support related decisions [5,6,7].

B. Neural Networks (NNs)

NNs are the most popular data mining techniques for regression analysis and have inherent capability to map nonlinear relationship between the input and output factors [3, 8]. Since there are nonlinear relationships between input factors and the kwh/move, NNs for regression are employed for modeling the relationships of related factors and the kwm/move levels of individual tool sets in a semiconductor fab. To investigate which approach will be most suitable for evaluating the relation between input factors and kwh/move of tool sets, we compared four representative NNs for regression task including back-propagation neural networks (BPNN), recurrent neural networks (RNN), radial basis function neural networks (RBFNNs), and support vector regression (SVR).

Back-Propagation Neural Networks (BPNN): BPNN are multilayer feedforward NNs with an input layer, an output layer and some hidden layers between the input and output layers.

Recurrent Neural Networks (RNN): Comparing to BPNN that are confined to static mapping, RNN contain feedback connections and can model the evolution of dynamic systems.

Radial Basis Function Neural Networks (RBFNNs): The major advantage of RBFNN over BPNN is the fast convergence [9]. The hidden layer neuron in RBFNN generally uses Gaussian basis function to transfer the inputs. The training in the hidden layer acts in an unsupervised way, unlike the supervised way in BPNN [10].

Support Vector Regression (SVR): SVR is a novel neural network algorithm based on the concept of support vector machine classifier [11]. The SVR learning minimizes an upper bound on the generalization error, as opposed to typical learning algorithms that minimize the error on the training data [12]. SVR has several advantages over other typical NNs, such as a global and unique solution and fast convergence [12, 13].

EMPERICAL STUDY

The data used for this study have been collected from 48 production tool sets of an 8-inch wafer foundry fab in Singapore; and the duration for data collection is 120 days. Take a tool set for example, Fig. 1 shows that the average kwh/move decreases nonlinearly as utilization gets higher. Hence, power consumption will be less if the variation of utilization is smaller given the same average utilization level.

Similarly, Fig. 2 implies that the larger the lot size, the less the kwh/move. In addition, kwh/move will be less if the variation of lot size is smaller. The factors mentioned above were for estimating the kwh/move levels of individual tool sets. By referring to Kuo [14] et al. (2011) and domain knowledge of the case fab, this study defined 19 factors that might affect the power consumption of individual tool sets in a semiconductor wafer fab, as shown in Table 1. Among them, 12 factors are related to mean value while the other 7 factors are related to variation. covered by the 15 input factors defined by Kuo [14] et al. (2011).

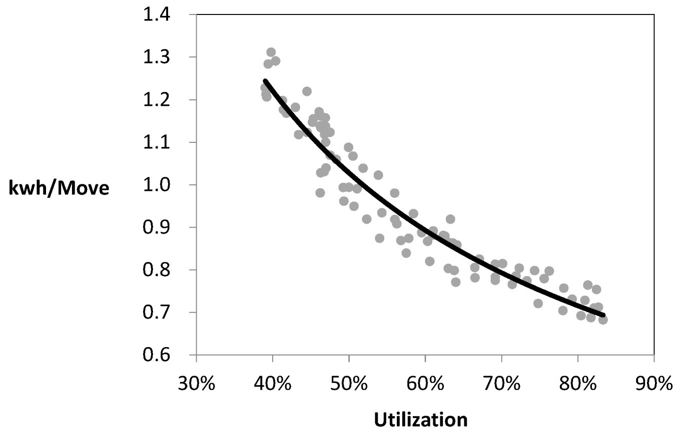

Fig. 1. Kwh per move vs. tool utilization

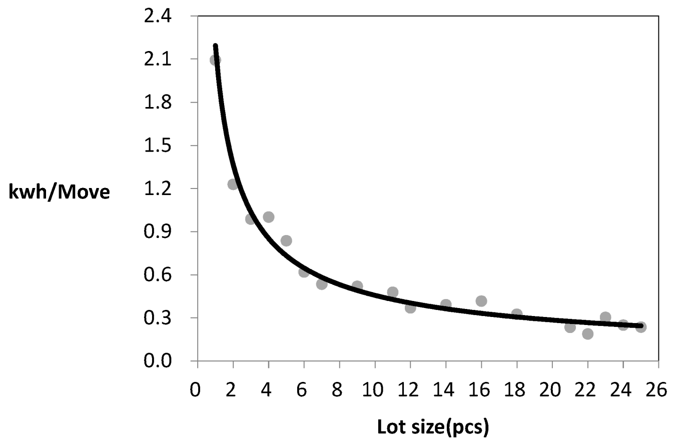

Fig. 2. Kwh per move vs. tool utilization

Mean	Variation
Mean limit for Q-time constraint	COV of process times
Mean lot size	Normalized COV of machine group loading
Mean move / hour / machine	Normalized COV of machine ID loading
Mean percentage of usable machines	Normalized Impact percentage of dispatching on COV of arrival rate
Mean same recipe rate	
Mean percentage of ENG lots	Normalized Intrinsic COV of arrival rate
Mean percentage of hot lots	Normalized STDEV of available rate
Mean percentage of super hot lots	Normalized STDEV of lot size
Mean process time	
Mean ratio for Q-time constraint	
Mean sampling rate	
Normalized Mean number of recipes	

Table 1. The input factors for estimating kwh/move

In this study, NNs are applied to analyze the relationships between related input factors and kwh/move of individual tool set in a fab. 4 learning algorithms for NNs are evaluated. And for each algorithm, different combinations of network architecture and parameters were experimented. We used the package of NeuroSolutions 5 (by Neurodimensions, Inc.) to develop the models of BPNN, RNN and RBFNN. The package of STATISTICA 7 (by STATSOFT, Inc.) was applied for SVR. The learning algorithms are evaluated with the least mean absolute percent error (MAPE) for testing data, as shown in Table 2. As a result, the best NNs method is back-propagation neural networks using Levenberg-Marquardt (LM) learning algorithm with number of hidden layer = 1 and number of hidden neurons = 3.

Tool set	BPNN	SVR	RNN	RBFNN
A	5.55%	9.69%	6.82%	21.34%
B	7.96%	10.02%	7.59%	17.35%
C	5.52%	9.96%	10.27%	16.02%
D	6.14%	6.25%	9.85%	20.85%
E	6.18%	7.33%	8.96%	20.11%
Average	6.27%	8.65%	8.70%	19.13%

Table 2. Comparison of MAPE for different NNs

Sensitivity analysis based on the trained NNs are conducted to estimate the saved power consumption in the fab per a specific percent, e.g. 10%, of improvement on each factor, as shown in Table 3. Table III also lists the managerial implications for improving individual factors so as to take actions for saving power consumption.

Factor	Relation with kwh	Reduced % for total kwh of the Fab per 10% improvement of the factor	Managerial implications
Mean process time	+	2.1200%	
Mean lot size	-	1.4767%	To merge or split lots until the mean lot size approach the optimal level
Mean percentage of usable machines	-	1.3380%	To relax tool dedication for non-critical products
COV of process times	+	0.9722%	
Mean same recipe rate	-	0.6881%	
Normalized STDEV of available rate	+	0.6141%	To balance non-available tool events among hours
Normalized STDEV of lot size	+	0.6023%	To merge or split lots until the mean lot size approach the optimal level
Normalized Impact percentage of dispatching on COV of arrival rate	+	0.5925%	To balance WIP profile by dispatching
Mean percentage of super hot lots	+	0.4913%	
Normalized COV of machine group loading	+	0.4543%	To optimize timing
Normalized Mean number of recipes	+	0.4321%	To simplify recipes
Normalized COV of machine ID loading	+	0.3270%	Optimal Schedule to sync PM/ENG with fluctuant coming WIP
Normalized Intrinsic COV of arrival rate	+	0.2530%	
Mean move / hour / machine	-	0.1877%	
Mean percentage of ENG lots	+	0.1731%	
Mean ratio for Q-time constraint	+	0.1223%	To eliminate unnecessary waiting time constrains
Mean limit for Q-time constraint	-	0.0958%	To relax the specification for waiting time constraint
Mean percentage of hot lots	+	0.0306%	
Mean sampling rate	+	0.0233%	

+ Positive relation, - Negative relation

Table 3. Relation between kwh and input factors, and their managerial implications

RESULT

Due to limited resources, a fab needs to prioritize the factors so as to save more power consumption with less effort. As shown in Table 4, the room for KPI improvement is defined by the gap between the as-is KPI value of the fab and the KPI value of the top 25 percentile of all the benchmark fabs that is provided by YouThought corporation. Then the Impact percent to total kwh of the Fab can be obtained by what-if analysis based on the room for KPI improvement for each factors. Table 4 shows that the case fab might save 17.37% power consumption if he aligned all the factors to the performance of the top 25 percentile of benchmark.

Priority	Factor	Factor Value As-is	Factor Value Benchmark P25	Room for Improvement %	Impact % to total kwh of the Fab
1	Mean percentage of usable machines	0.533	0.829	55.69%	4.41%
2	Normalized STDEV of available rate	0.071	0.025	65.07%	2.25%
3	Mean process time	1.820	1.630	10.44%	2.18%
4	Mean lot size	20.798	23.526	13.12%	1.78%
5	Mean percentage of super hot lots	0.018	0.007	62.70%	1.76%
6	Normalized Mean number of recipes	18.192	6.981	61.63%	1.53%
7	Normalized Intrinsic COV of arrival rate	0.433	0.121	71.99%	1.00%
8	Normalized COV of machine group loading	0.166	0.123	25.84%	0.88%
9	Normalized COV of machine ID loading	0.433	0.333	23.22%	0.59%
10	Mean limit for Q-time constraint	6.040	9.953	64.78%	0.35%
11	Mean ratio for Q-time constraint	0.274	0.208	24.08%	0.23%
12	Mean same recipe rate	0.614	0.606	1.29%	0.17%
13	Normalized STDEV of lot size	3.565	3.522	1.20%	0.14%
14	Mean percentage of hot lots	0.094	0.063	32.87%	0.07%
15	Mean sampling rate	0.689	0.522	24.20%	0.04%
16	Normalized Impact percentage of dispatching on COV of arrival rate	0.702	1.332	0.00%	0.00%
17	COV of process times	0.307	0.313	0.00%	0.00%
18	Mean percentage of ENG lots	0.016	0.017	0.00%	0.00%
				Total	17.37%

Table 4. Prioritized factors for improvement

By the same way, the tool sets can also be prioritized for each factor. As shown in Table 5, the top 21% tool sets (10 / 48 tool sets) account for 70.3% (3.10%/4.41%) the impact to total kwh of the fab for the factor "Mean percentage of usable machines", which means the percentage of released tools in this semicounductor processed step.

This study has demonstrated how to apply NNs to estimate the kwh/move of individual tool sets, and to analyze the relationships between kwh/move and individual input factors. An empirical study was conducted by using the equipment data of a real fab. The results showed that the proposed approaches can discover rich opportunities for saving power consumption by production tools.

Priority	Module	Tool set	Factor Value As-is	Factor Value Benchmark P25	Room for Improvement %	Impact to Tool kWh/day	Impact % to total kwh of the Fab	Accu.
1	Thin film	T7	0.491	0.844	71.71%	290.3	0.65%	0.65%
2	Dry etch	T2	0.518	0.763	47.30%	230.6	0.52%	1.17%
3	Thin film	T3	0.543	0.844	55.39%	199.1	0.45%	1.61%
4	Implant	T11	0.539	0.583	8.22%	153.1	0.34%	1.95%
5	Implant	T10	0.490	0.583	19.03%	119.5	0.27%	2.22%
6	Thin film	T5	0.772	0.844	9.23%	108.8	0.24%	2.46%
7	Photo	T14	0.592	0.673	13.81%	93.7	0.21%	2.67%
8	Dry etch	T21	0.723	0.763	5.50%	75.6	0.17%	2.84%
9	Thin film	T17	0.742	0.844	13.66%	74.1	0.17%	3.01%
10	CMP	T8	0.817	0.862	5.48%	41.5	0.09%	3.10%
...	...	...	...	...	...	...	...	...
39	Implant	T35	1.706	0.583	0.00%	0.0	0.00%	4.41%
48	Furnace	T26	1.004	0.867	0.00%	0.0	0.00%	4.41%

Table 5. Prioritized tool sets for the factor of "Mean percentage of usable machines"

REFERENCES

[1] Energy use in the semiconductor manufacturing industry. Washington DC: United States Environmental Protection Agency, 1998.

[2] S.-C.Hu and Y.K. Chuah, "Power consumption of semiconductor fabs in Taiwan," *Energy*, vol. 28, issue 8, pp 895-907, June 2003.

[3] K. A. Smith and J. N. D. Gupta, "Neural networks in business: Techniques and applications for the operations researcher," *Comput. Oper. Res.*, vol. 27, no. 11, pp. 1023–1044, 2000.

[4] U. Fayyad, G. Piatesky-Shapiro, and P. Smyth, "The KDD process for extracting useful knowledge from volumes of data," *Commun. ACM*, vol. 39, no. 11, pp. 27–34, 1996.

[5] C.-F. Chien and L. Chen, "Using rough set theory to recruit and retain high-potential talents for semiconductor manufacturing," *IEEE Trans. Semicond. Manuf.*, vol. 20, no. 4, pp. 528–541, 2007.

[6] C.-F. Chien, W. Wang, and J. Cheng, "Data mining for yield enhancement in semiconductor manufacturing and an empirical study," *Expert Systems With Applications*, vol. 33, no. 1, pp. 192–198, 2007.

[7] S.-C. Hsu and C.-F. Chien, "Hybrid data mining approach for pattern extraction from wafer bin map to improve yield in semiconductor manufacturing," *Int. J. Prod. Econ.*, vol. 107, no. 1, pp. 88–103, 2007.

[8] M. Chambers and C. A. Mount-Campbell, "Process optimization via neural network metamodeling," *Int. J. Prod. Econ.*, vol. 79, no. 2, pp. 93–100, 2002.

[9] J. F. Briceno, H. El-Mounayri, and S. Mukhopadhyay, "Selecting an artificial neural network for efficient modeling and accurate simulation of the milling process," *Int. J. Mach. Tools Manuf.*, vol. 42, no. 6, pp. 663–674, 2002.

[10] B. Kim and K. Park, "Modeling plasma etching process using a radial basis function network," *Microelectronic Eng.*, vol. 77, no. 2, pp. 150–157, 2005.

[11] K. Kim, "Financial time series forecasting using support vector machines," *Neurocomputing*, vol. 55, no. 1–2, pp. 307–319, 2003.

[12] W. Chen and J. Shih, "Comparison of support-vector machine and back propagation neural networks in forecasting the six major Asian stock markets," *Int. J. Electron. Fin.*, vol. 1, no. 1, pp. 49–67, 2006.

[13] E. Byvatov, U. Fechner, J. Sadowski, and G. Schneider, "Comparison of support vector machine and artificial neural network systems for drug/nondrug classification," *J. Chem. Inf. Comput. Sci.*, vol. 43, no. 6, pp. 1882–1889, 2003.

[14] Kuo, C. J., Chien, C. F., & Chen, J. D., "Manufacturing Intelligence to Exploit the Value of Production and Tool Data to Reduce Cycle Time," *IEEE Transactions on Automation Science and Engineering*, vol. 8, Issue 1, pp. 103-111, 2011.

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