A Methodology to Optimize Value in Discrete Event imulation for Production Planning and Control Studies

NurAmalina Muhammad and Chin JengFeng
School of Mechanical Engineering
University Sains Malaysia
Engineering Campus 14300 NibongTebal, Pulau Pinang, Malaysia

Abstract

Production planning and controlis an important aspect in manufacturing industry in order to achieve the target of production such as high quality products, on-time delivery and increasing profit. Inappropriate setting of the values for each variable will lead to the failure of the production. The aim of the paper is to develop a clear methodology of important steps during finding the optimal value of the input variables. The methodology is presented in form of framework, in which four approaches are highlighted that consists of discrete-event simulation, analysis of variance, polynomial regression and response surface methodology. The framework is applied to a production planning and control problem in the case study based on the semiconductor manufacturing company. The framework works well with the case study, reduce the time consuming and improve the production by achieving better optimal value of variables.

Keywords
Discrete-event simulation, optimal value, polynomial regression, production planning and control, response surface methodology

1. Introduction

Production planning and control system plays an important role in a manufacturing industry. Every stage of conversion raw materials into finished products needs a meticulous production planning such as scheduling, dispatching, inspection, and inventory management, to ensure that the company can achieve required production target and optimize the utilization of resources. Unfortunately, management often faces the difficulties in determining and applying the appropriate and accurate values of variables in the production to achieve the aforementioned targets. For an example, semiconductor manufacturing may be hard to decide accurate level of control variables such as lot size of wafer, setup time and lot sequence to meet production goals such as average work-in-process, utilization, average flow time and service level. These difficulties lead to adoption of discrete-event simulation (DES) concept to study and experiment the internal interactions within a complex system (Werker et al., 2009). By mimicking the real world of process, they are freely to change the simulation inputs and observe the resulting outputs while producing valuable insight into the most important variables and into how these variables interact. DES received great attention since forty years ago and it has grown popularity steadily to be now recognized as the most frequently used across a range of industries (Hollocks, 2006). Utilizing DES solely is less precise to support the understanding on the simulation result. Thus, Integrating DES with the response surface methodology (RSM) may yield more critical insights into an investigated production planning and control problem.

Literature studies of integration DES and RSM (DES-RSM) are available in many areas of application such as failure analysis, material handling system, scheduling of dispatching rules and logistics network. Sajadi et al. (2011) adopted stochastic optimal control theory, DES, experimental design and automated RSM to control the production rate of the machines. Zhang et al. (2009) examined the result of proposed dynamic bottleneck dispatching policy in order to evaluate and optimize of dispatching rules. Lin et al. (2003) analyzed the performance of connecting transport automated material handling (AMHS) in wafer fab. Lin et al. (2005) optimized the desirability function that is the combination of multiple attributes of the products while parameterized dispatching rules. Prakash and Chin (2011) studied the behavior of multiple types of pull system by using DES-RSM.

Despite many studies have been applied DES-RSM in different areas, the importance of main steps of each approach was not fully explained in those papers. Their explanation in the paper is more focusing on the result of experiments rather than explanation of the detail methodology of simulation. The main aim of this paper is to develop a clear explanation of important steps during performing DES-RSM in production planning and control system. The framework consists of methods such as DES, Analysis of Variance (ANOVA), and RSM. Each method will be provided a clear explanation in the following section in order to achieve the objective of this paper. The arrangement of this paper is as followed: Section 2 will discuss about the overview of DES-RSM, Section 3 will provide a DES-RSM framework and Section 4 will be the case study of DES-RSM framework and conclusion in the Section 5.

2.Overview of DES-RSM

2.1 Discrete-Event Simulation (DES)

Discrete-event simulation (DES) is the modeling of systems in which the state variable changes only at a discrete set of points in time (Banks et al., 2005). Fine tuning of variable values instant in time will mark a change of state in the system. DES can be stimulated by several softwares for different areas of studies such as Arena, AutoMod, Extend, Flexsim, Micro Saint, ProModel and WITNESS. The simulation models are analyzed by numerical methods rather than by analytical methods. Numerical methods employ computational procedures to solve mathematical models while analytical methods employ the deductive reasoning of mathematics to solve the model. Simulation can be used for the following purposes (Gunal and Mike, 2010):

- To study the internal interaction of a complex system and observe the effect of alterations towards the model's behavior for different point of views. In simulation, given a particular set of inputs and model characteristics either mimicking the real or design system, the model is run while stimulated behavior is observed. This process of changing inputs and model characteristics results in many advantages to the industry.
- To experiment the new ideas before implementation, so as to prepare for what might happen. New policies, procedures and flow can be explored without disturbing ongoing operations of the real system, while new design, physical layouts and transportation system can be tested without committing resources for their acquisition.
- To design simulation models for training purpose without consuming extra cost and disrupting the real process. A simulation study can assist in understanding how the system operates instead of how individuals think the system operates.

2.2 Analysis of Variance (ANOVA)

Analysis of variance (ANOVA) is defined as the statistical method that is used to test the variability in data between groups of population sample means in order to generalize the inequality among the population means (Narayanagounder et al., 2009). It is often used for testing the hypotheses that there is no difference between a numbers of populations. The objective of ANOVA is to determine whether mean differences between the populations from which the samples were obtained are justified with the mean differences that achieved for the sample data. ANOVA is a particular form of statistical hypothesis testing heavily applied in the design and analysis of experimental data (Zwaneburg et al., 2011). A statistical hypothesis test is a technique of making decisions using analysis data.

There are two types of ANOVA called one-way ANOVA and two-way ANOVA. One-way ANOVA is applied to test a single variable with two or more independent variable and two-way ANOVA is extension of it that involves only two factors of variable (Turner and Julian, 2001). Detail framework of ANOVA will be discussed in Section 3.

2.3 Polynomial Regression

The relationship between the output variables and input variable can be analyzed by using polynomial regression in a form of linear regression and modeled as an *n*th order polynomial. The main advantages of polynomial regression are the ability to represent a variety of relationship and the measured point will be approximated until satisfied by increasing the higher order terms (Brown et al., 2007). The higher order of polynomial increases the number of fitting degrees between regression equations and data. A higher number of degree orders reduces the precision of regression equation and affects the likelihood to obtain optimal values (Fang and Long, 2012). In this paper, we consider on second degree of regression.

2.4 Response Surface Methodology (RSM)

Response surface methodology (RSM) is a collection of statistical and mathematical procedure based on the fit of a polynomial equation from regression polynomial method to the experimental simulation data (Bezerra et al., 2008).

The objective of RSM is to obtain an optimal output variable by making changes to the several input variables by using a sequence of designed experiments to attain the best system performance. The variable that chosen in the RSM is based on the result of ANOVA as previously described. This is to intensify the result obtained by simulation before being applied to the system. The main advantage of RSM is simplified relationship that can be used for practical engineering purposes which lead to reduce analysis cost and time consuming (Zangeneh et al., 2002).

3.DES-RSM Framework

Performing simulation in production planning and control requires systematic execution of steps in order to determine the optimal values. In this paper, a framework termed as DES-RSM is conceived to provide logical connection of these steps, including problem formulation, discrete-event simulation, analysis of variance, polynomial regression, response surface methodology and control analysis. The framework is presented in Figure 1.

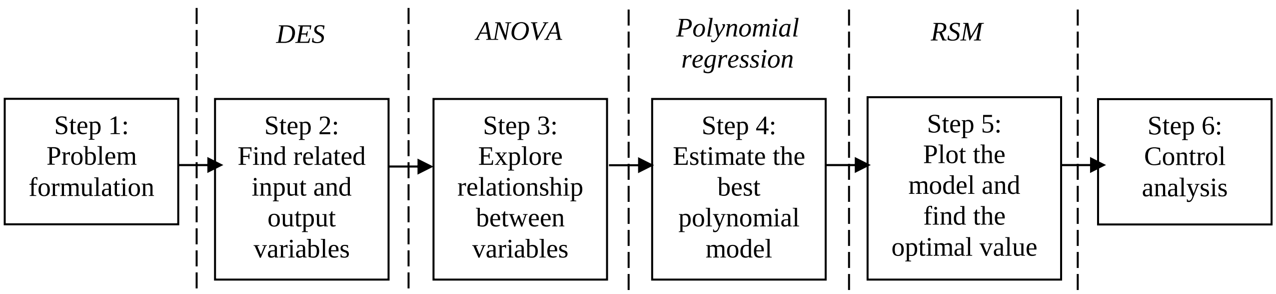

Figure 1: DES-RSM framework

Step 1: Problem Formulation
The problem of production planning and control is excavated with the detail specification. Problem is derived based on the failure occurred on the production job-shop and the reduction of production performance. Decreasing throughput per day, higher bottleneck and high cost are the common problems of production planning and control. Brainstorming session should be done in deriving the problem related to production planning and control in order to find the real root cause that affect the problem.

Step 2: Find related input and output variables
The objective of this step is to find the related measure of input variable of the problem that can affect the result of output variable. Basically, the input variables can be lot size, inter-arrival times, service times, setup time or queue length while output variables can be machine utilization, flow time, cycle time, average work-in-process (WIP) or cost. Real-world simulation models are rather large, and the amount of data stored is vast, so such run usually conducted with the aid of computerized system. During developing a model for simulation, the model user supposed to have better understanding regarding the overall steps in simulation study as depicted in Figure 2 (Banks et al., 2005).Then, other steps that are considered important in discrete-system simulation are:

- Determine the characteristics of all inputs of the simulation. Basically, these are modeled as probability distributions.
- Construct a simulation table. The simulation table provides a systematic method for tracking system state over time.
- Find a suitable warm-up time and runtime for the simulation to process the model. Warm-up is needed because normally started with no parts in any of the machine in order to get steady-state performance of measure.
- Generate iteration process for each of the input; evaluate the function and calculating a value of the output.

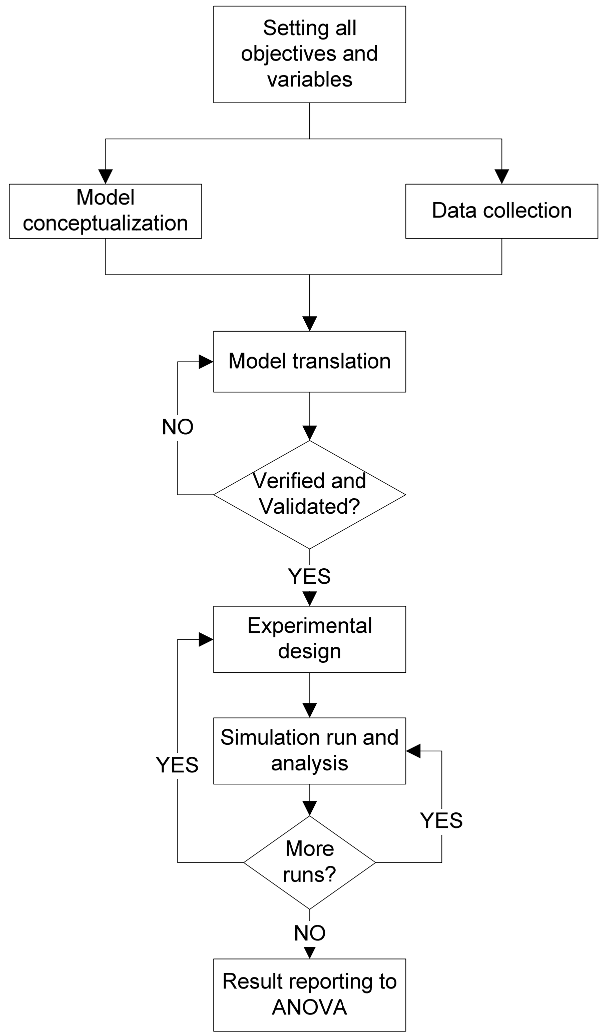

Figure 2: Steps of simulation study

Results are generated at the end of the simulation. The size of the data collected depends on the number of iterations and input parameters provided. This will lead to the difficulties to determine the optimal values in relation to the problems of production planning and control under study. ANOVA is adopted to analyze the result of simulation and scope down the relationship between input and output variables.

Step 3: Explore relationship between variables
ANOVA is used to determine whether there are any significant differences between the means of two or more input variables used in the simulation previously. In this step, we only consider on one-way ANOVA. One-way ANOVA is used when comparing two or more group means on a continuous dependent variable. The important step before performing ANOVA is to make sure that the data from the simulation result passes the assumptions that required for a one-way ANOVA. The assumptions that must be concerned during performing the ANOVA method are (Dowdy et al., 2011):

- The observations made must be independent of one another.
- The population variances in each group are the same.
- The observations in each group come from a normal distribution.

The major concepts that considered important in performing ANOVA is the calculating sums of squares (SUM), degree of freedom (DF), mean square (MS), F-ratio and F-critical. The steps in performing ANOVA are presented in Figure 3.

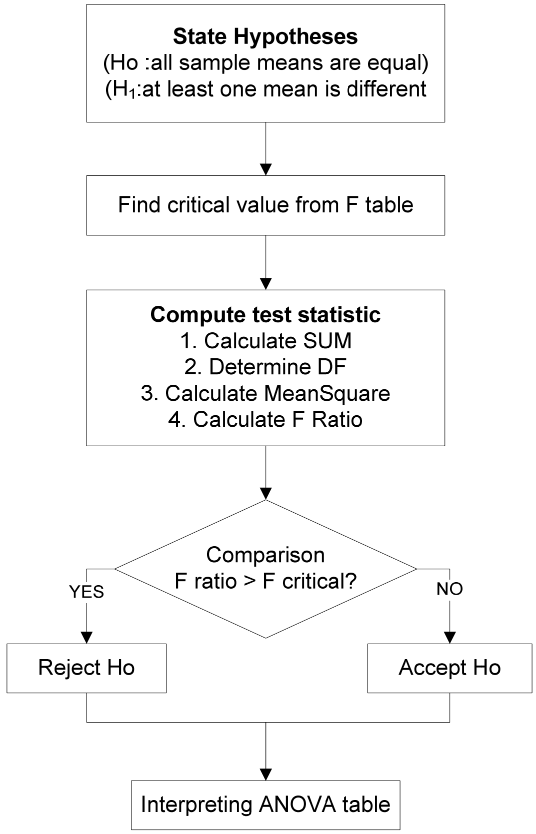

Figure 3: Steps in ANOVA study

The rejection of null hypothesis can be concluded as a significant difference among the groups, whereas fail to reject the null hypothesis falls under no significant difference among the groups. Then, the methodology in optimizing values of simulation is continued in response surface methodology by using regression method as explained in the following step.

Step 4: Estimate the best polynomial model

In this step, the mathematical procedure is represented in order to find the best polynomial model of the problem. Polynomial regression is the most suitable approach to perform this step. Here are some approaches of statistics that can be considered during regression (Asaro et al., 2007; Narasimhan and Das, 2001)

- **R-square and Adjusted R-square**
  R-square and adjusted R-square must be as high as possible to the perfection of regression line. A higher R-square means that most of the variance is covered by the regression model. An R-square of 0.7 and above is generally accepted as good.
- **P-value**
  P-value should be as low as possible to possibility to reject the null hypothesis. The value of 0.05 and lower for P-value would be better.
- **Durbin Watson**
  The Durbin Watson is used to test the first order serial correlation among residuals in a linear model. A value less than 0.80 usually indicate that correlation is likely.

Polynomials model either first-order polynomial or second-order polynomial is selected after considering all the statistics. In this paper, second-order model is more preferable than a straight line of first-order model in order to optimize the value of variables. The selected polynomial model is shaped on the fitted curved and analysis is explained in the following step.

Step 5: Plot the model and find the optimal value
RSM is functioned to explore the plotting relationship between input variables and output variables from previous steps by using design of experiments in order to obtain optimal values. This is a quantitative procedure to quantify how an output variable depends on input variables. The choice of the design of experiments can have large effects on the accuracy of the approximation of constructing the response surface. Now, we can answer the question of "What specific levels of important variables produce an optimum values?" by interpreting the polynomial model in many ways. There are can be parabola graph, contour graph, Pareto chart and etc. The design of experiments can be tests until response reach the optimal values either minimum or maximum values of output variables.

Step 6: Control analysis
The optimal values can be implemented in the real world to achieve the target of throughput or compare with the previous values for the improvement of the production. It is because the optimal values of output variables will be vary over a specific period of time. The development of the optimal values must be continuously done in order to keep the production is on the track and achieve the target. If the same new problem arises again, the steps should be restarted again to identify the new optimal value of variables.

From the methodology of DES-RSM framework, a case study is conducted in a semiconductor manufacturing company. The application of the framework will be discussed briefly in the next section.

4.Case Study

A case study was conducted in a semiconductor industry situated at Malaysia. In the semiconductor manufacturing especially wafer fabrication, the complexity of re-entrant process flow, large number of process steps and high mix of product types in low volume become a tremendous challenge for the team to determine the accurate planning of production. From the historical data, the cycle time to produce a complete wafer becomes longer than the available planning. This leads to the late delivery and reduces the satisfaction of customers. The factors of the increasing cycle time that can be seen during the production are higher bottleneck at the critical machines, idleness for a long period time and decreasing throughput per month. Higher bottleneck tends to increase the waiting time of the wafer in front of the machines before being process. In wafer fabrication, the waiting time is the biggest contribution of increasing cycle time due to the aforementioned complexity of the process.

The management team decided to investigate the root cause of the problem. The brainstorming session between the team members arrived at conclusion to perform a methodology of DES-RSM framework in order to reduce the cycle time of the wafer fabrication. The WITNESS simulation softwarewas adopted to interpret the real world of production into DES model and to observe the interaction of the complex system, with focus onthe real input variables that affect the cycle time of the wafer fabrication. The team decided to examine two input variables called A and B to find the correlation in the cycle time studies. After the simulation run and data collection, the significant difference and relationships between these variables with the cycle time are studied through ANOVA. The table shows that the entire hypothesis are rejected and it means that A and B are significant different with the cycle time. Then, each statistics in polynomial regression was considered todetermine the suitable polynomial model for variable A and B. With the value of R-square above 0.7, the polynomial model of A is accepted. For B, the value of R-square is below 0.7 and the model is rejected. Nevertheless, the polynomial model of B was revealed to be best represented by the AxB model,with A assumes constant. The chosen models are plotted by RSM and the optimal values of A and B can be estimated from the plotted graph. The graphs show that the cycle time can be reduced at optimal values 0.5 of A and 0.4 of B. The finding can update and be implemented to the real production. The comparison of previous value and current values must be done for the control analysis and improvement purposes. The DES-RSM framework of the case study is illustrated in the Figure 4.

The implementation of DES-RSM framework in this case study provides clear view and detailed descriptions to each step, thus eases the user to configure an approximate statistics of the framework based on the existing problem setting. The needed time to accuratelyfind the optimal value can be shortening.

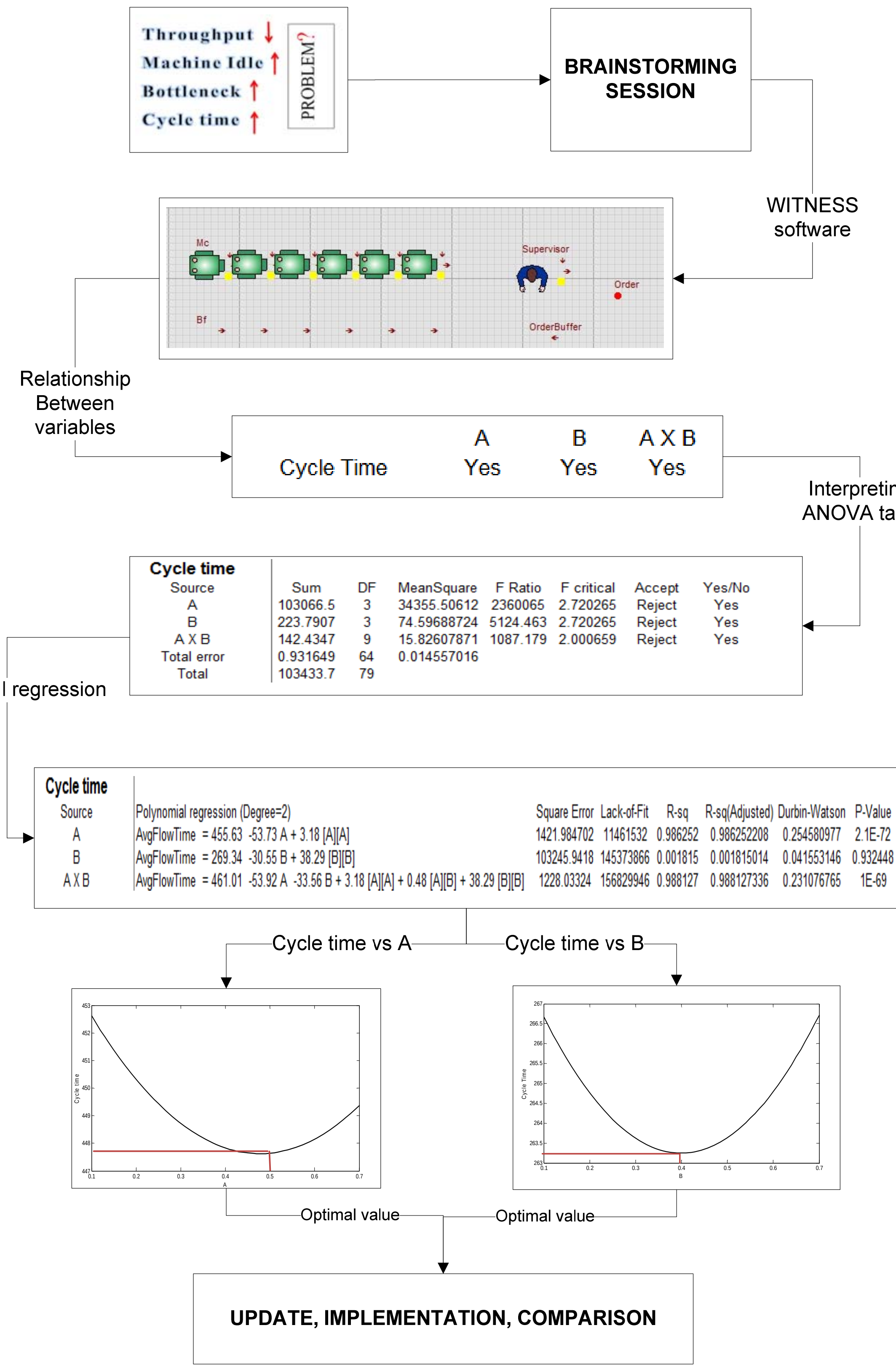

Figure 4: Framework of case study

5.Conclusion

A systematic methodology in finding the optimal value based on the production planning and control problem is presented in this paper. The proposed framework works well with the problems by following each step in the framework and achieves required optimal value of the input variables that compatible with the output variables. As a conclusion, the related variables can be determined by using DES, ANOVA estimates the relationship between variables and polynomial regression sets the model of variables. RSM plots the model into the perfect curve and optimal value of the variables is achieved. Implementation the proposed framework in the case study also concludes that the framework can reduce the time consume, ease of use and able to apply in widely area of application.

Acknowledgement

The authors wish to acknowledge UniversitiSains Malaysia (USM) for the full financial support through the "Delivery Excellence" grant no.910345 and Short term grant no:60311042.

References:

Asaro, P. V., Lewis, L. M., and Boxerman, S. B., The impact of input and output factors on emergency department throughput. *Academic Emergency Medicine*, vol. *14, no.* 3, pp. 235-242, 2007.

Banks, J., Carson, J. S., Nelson, B. L., and Nicol, D. M., Discrete-event system simulation, 4th Edition, Pearson Prentice Hall, 2005.

Bezerra, M. A., Santelli, R. E., Oliveira, E. P., Villar, L. S., and Escaleira, L. A., Response surface methodology (RSM) as a tool for optimization in analytical chemistry. *Talanta*, vol. *76*, no. 5, pp. 965-977. 2008.

Brown, S. A., Venkatesh, V., and Goyal, S., (Expectation confirmation in technology adoption: An examination of six competing theoretical models. In *Under Review, available from:http://misrc.umn.edu/workshops/2007/spring/Susan.pdf*. 2007.

Dowdy, S., Wearden, S., and Chilko, D., *Statistics for research*. 3rd Edition, Wiley-Interscience, 2011

Fang, W., and Long, W., Polynomial regression fitting analysis on influencing factors for printing ink transfer rate. In *Intelligent Control, Automatic Detection and High-End Equipment (ICADE), 2012 IEEE International Conference on* (pp. 9-13).IEEE, 2012.

Günal, M. M., and Pidd, M., Discrete event simulation for performance modelling in health care: a review of the literature. *Journal of Simulation*, vol. *4*, no. 1, pp. 42-51, 2010.

Hollocks, B. W., Forty years of discrete-event simulation—a personal reflection, Journal *of the Operational Research Society*, vol. *57*, no. 12, pp. 1383-1399, 2005.

Lin, J. T., Wang, F. K., and Wu, C. K., Simulation analysis of the connecting transport AMHS in a wafer fab. *Semiconductor Manufacturing, IEEE Transactions on*, vol. *16*, no. 3, pp. 555-564, 2003.

Lin, J. T., Wang*, F. K., and Kuo, P. C., A parameterized-dispatching rule for a logic IC sort in a wafer fabrication. *Production Planning & Control*, vol. *16, no.* 5, pp. 426-436, 2005.

Narasimhan, R., and Das, A., The impact of purchasing integration and practices on manufacturing performance. *Journal of Operations Management*,*19*(5), 593-609, 2001.

Narayanagounder, S., and Gurusami, K, A new approach for prioritization of failure modes in design FMEA using ANOVA. *World Academy of Science, Engineering and Technology*, vol. *49*, no. 524-31. 2009.

Prakash, J., and Chin, J. F., A comparison of push and pull production controls under machine breakdown. *International Journal of Business Science and Applied Management*, *6*, 2011.

Sajadi, S. M., Esfahani, M. M. S., and Sörensen, K., Production control in a failure-prone manufacturing network using discrete event simulation and automated response surface methodology. *The International Journal of Advanced Manufacturing Technology*, vol. 53, no. 1-4, pp. 35-46, 2011.

Turner, J. R., and Thayer, J., Introduction to Analysis of Variance: Design, Analyis& Interpretation. SAGE Publications, Incorporated, 2001.

Werker, G., Sauré, A., French, J., and Shechter, S., The use of discrete-event simulation modelling to improve radiation therapy planning processes.*Radiotherapy and Oncology*, vol. *92*, no.1, pp. 76-82, 2009.

Zangeneh, N., Azizian, A., Lye, L. M., and Popescu, R., Application of response surface methodology in numerical geotechnical analysis. In*Proceedings 55th Canadian Geotechnical Conference, Niagara Falls, Canada*, 2002.

Zhang, H., Jiang, Z., and Guo, C., Simulation-based optimization of dispatching rules for semiconductor wafer fabrication system scheduling by the response surface methodology. *The International Journal of Advanced Manufacturing Technology*, vol. *41*, no. 1-2, pp. 110-121, 2009.

Zwanenburg, G., Hoefsloot, H. C., Westerhuis, J. A., Jansen, J. J., and Smilde, A. K., ANOVA–principal component analysis and ANOVA–simultaneous component analysis: A comparison. *Journal of Chemometrics*, vol. *25*, no. 10, pp. 561-567, 2011.

Biography

Nur Amalina Muhammad received her Beng (Hons) degree in Manufacturing Engineering with Management from UniversitiSains Malaysia in 2012. Currently, she is an MSc (Research) candidate in School of Mechanical Engineering at the University Sains Malaysia. Her research interest is on simulation of manufacturing system and production planning and control system.

Chin JengFeng obtained his Doctor of Philosophy (Ph. D) from University of Birmingham, UK and currently is a senior lecturer in the School of Mechanical Engineering, UniversitiSains Malaysia. The research areas of interest include production planning and control, lean manufacturing and intelligent manufacturing system.