DYNAMIC CONTROL FOR BATCH PROCESS SYSTEMS
USING STOCHASTIC UTILITY EVALUATION

A Dissertation

by

HONGSUK PARK

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2011

Major Subject: Industrial Engineering

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Approved by:

Chair of Committee,	Amarnath Banerjee
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ABSTRACT

Dynamic Control for Batch Process Systems Using Stochastic Utility Evaluation.

(August 2011)

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Chair of Advisory Committee: Dr. Amarnath Banerjee

Most research studies in the batch process control problem are focused on optimizing system performance. The methods address the problem by minimizing single criterion such as cycle time and tardiness, or bi-criteria such as cycle time and tardiness, and earliness and tardiness. This research demonstrates the use of Stochastic Utility Evaluation (SUE) function approach to optimize system performance using multiple criteria.

In long production cycles, the earliness and tardiness weight (utility) of products vary depending on the time. As the time approaches the due-date, it affects contractual penalties, loss of customer goodwill and the storage period for the completed products. It is necessary to reflect the weight of products for earliness and tardiness at decision epochs to decide on the optimal strategy. This research explores how stochastic utility function using stochastic information can be derived and used to strategically improve existing approaches for the batch process control problem.

This research first explores how SUE function can be applied to existing model for bi-objective problem such as cycle time and tardiness. Benchmark strategies using SUE function (NACH-SUE, MBS-SUE, No idle and full batch) are compared to each other. The experimental results show that NACH-SUE effectively improves mean cycle time and tardiness performance respectively than other benchmark strategies.

Next, SUE function for earliness and tardiness is used in an existing model to develop a tri-objective problem. Typically, this problem is very complex to solve due to its trade-off relationship. However SUE function makes it relatively easy to solve the tri-objective problem since SUE function can be incorporated in an existing model. It is observed that SUE function can be effectively used for solving a tri-objective problem. Performance improvement for averaged value of cycle time, earliness and tardiness is observed under a comprehensive set of experimental conditions.

To Sook Young for her love, sacrifice and support

too good for me.

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Finally, I would like to give all my thanks to God, who is always faithful to listen and answer my prayers.

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CHAPTER I

INTRODUCTION

Scheduling problems with cycle time, earliness and tardiness measures have been studied broadly in the last fifty years due to the emergence of Just-In-Time (JIT) production approaches in industry. JIT strategies emphasize production scheduling of jobs such that finished products are delivered exactly on time. Early delivery leads to potential extra holding cost for the completed products, while on the other hand, late delivery can potentially cause lost sales and loss of consumer good will. Therefore, when JIT scheduling is considered, the jobs have to be completed as close to the due date as possible and cycle time is minimized as much as possible.

The semiconductor industry has continued to be an important field of research in recent years because of the widespread use of integrated circuits (IC) in devices ranging from personal computers to high-tech electronics. Due to the growth of the semiconductor market, research in IC fabrication technology and methodology is steadily expanding.

Wafer production is a very complex process with a long production cycle; and much of the complexity results from batching, time-step, and sequencing problems at several stages of the cycle.

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This dissertation follows the style of *IIE Transactions*.

The majority of problem-solving methods attempt to minimize production attributes such as cycle time, earliness and tardiness (Mathirajan and Sivakumar (2006a)). Most often, the batch process itself is the bottleneck, particularly since competing factors come into play the important decision to run a partial batch versus waiting for future arrivals to form a full batch.

On-time delivery and rapid production of wafers are the two critical factors affecting the retention of customers and influencing the performance of manufacturer. Diffusion furnaces are the most commonly used batch processors in semiconductor production. Yet while they can handle a batch of products concurrently, their processing times are too slow compared to serial processors that handle one product at a time. This dissertation analyzes forthcoming performance-enhancing measures in the decision-making phase of batch processing that aid in controlling batch processors.

At the decision epoch, most models use the static weight for product type however if earliness and tardiness are considered at the decision point, the dynamic weight for product type needs to be estimated according to stochastic information in the long-run control of a batch processor and multiple product types.

The purpose of this dissertation is to develop a SUE function to provide the weight for product type at each decision point. The focus is on performance improvement considering multi-criteria with the use of SUE function in existing model.

1.1 Overview of the problem

Diffusion furnaces, the most commonly used batch processors in the wafer fabrication (hereafter wafer fab) phase, support the processing of a standard lot of wafers to be processed concurrently. However, their use presents four key constraints: 1. it is not possible to process different types of products simultaneously due to the chemical nature of the procedure; 2. generally, 6 to 8 products can fit into a furnace in a single turn; 3. once in operation, it is not possible to shut down a furnace, e.g., to take corrective measures; and 4. batching takes approximately 5 to 10 times longer than serial processing.

Products can be processed either as a full batch (the maximum number of products, i.e. the full capacity of the processor) or as a partial batch. The full batch condition poses fewer decision-making problems since management is needed only to determine which product type has priority in processing. For partial batch conditions, however, management must decide whether to process the partial batch, wait for completion of the batch if the batch processor is ready for use, and the order of priority.

Dynamic control strategy is the term describing the principles that govern every "decision point" in a system. In batch processing, decisions are made – which product type to process first based on data concerning the current status of products in queue, status of product batches at all the stations, time limitations in which the execution of the decision becomes possible – only at the time a batch processor becomes available for use. The anticipation of the readiness of the batches of a particular product type when a batch processor becomes available is the critical factor in implementing dynamic control strategy. Time is of the essence, for the faster the process, the quicker the semiconductors will be manufactured and delivered to customers. Hence, the cycle times of the wafer fab phase are critical. However, if earliness and tardiness are considered, even though cycle time is getting longer, all criteria (cycle time, earliness and tardiness) should be considered as a multi-objective problem.

This dissertation focuses on the administrative side of wafer fab manufacturing by discussing the issues that accompany the reduction of cycle times and on-time delivery. Rather than examining day-to-day affairs, we look at a manufacturer's monthly or quarterly objectives vis-à-vis the mean cycle times and mean earliness/tardiness issues related to batch processors. Data concerning the status of the batch products is vital for making decisions about batch processor utilization. The use of a serial processor before the batch processor gives an accurate representation of the serial processor timings which in turn allows management to better calculate batch processor response times and the stochastic data. In other words, developing a clear control strategy will enhance batch processor efficiency.

This dissertation also looks at many of the variables associated with the control strategy of a serial processor that need to be addressed to improve efficiency. They include the number of products, the product mix, the batch processor's capacity for individual product types, the traffic intensity of the batch processor. The effect of these characteristics on the performance is also this dissertation's issue.

1.2 Research objectives

The research is designed to accomplish three objectives:

i) Develop a SUE function to solve bi/tri-criteria problems;

ii) Illustrate how the SUE function can be combined with existing approaches

iii) Show how the SUE function operates and performs in the existing function by comparing the performances of full batch policy, no-idle policy, MBS-SUE and NACH-SUE. Simulations for cycle time and tardiness are performed. Following the approach for bi-criteria, it is extended to solve the tri-criteria problem for cycle time, earliness and tardiness.

1.3 Significance of the research

A rich body of knowledge primarily in the form of heuristics appears in the literature about techniques to minimize overall cycle time, earliness and tardiness. In a long production cycle time system, when simultaneously considering cycle time, tardiness and earliness criteria, the weight of commodities for earliness and tardiness can change depending on the time. Due date and storage cost are critical factors: when tardiness is considered as a criterion, it can adversely affect contractual obligations in the form of penalties, or dissatisfied customers switching to competitors (Panwalkar and Smith 1982; Wu and Wang 1999) and when earliness is considered as a criterion, it can affect storage cost. For example, the price of commodities is fixed for all processing periods; however, after the due date, additional cost or value must be considered along with the loss of customer good will and other factors associated with not fulfilling contractual obligations. On the other hand, additional cost for storage must be considered when jobs are completed too soon. There is also an additional cost factor associated with contamination during storage, particularly in semiconductor manufacturing. This dissertation considers the changing weight for earliness and tardiness as "utility" and theorizes that the weighted values are useful when choosing the optimal production strategy in a long production cycle time system with changing weight of commodities for earliness and tardiness.

A stochastic utility evaluation (SUE) function is introduced to incorporate the weight for earliness and tardiness. The SUE function is generated by the information at a decision epoch from the arrival distribution of commodities, due date and the number of remaining orders. As the time approaches due date, the weight for tardiness parameter increases. On the other hand, the weight for earliness parameter drops since the period for keeping in storage shortens.

Among the commonly used optimal production strategies, Minimum Batch Size (MBS) (Van Der Zee *et al*. (1997)) and Next Arrival Control Heuristic (NACH) (Fowler *et al*. (2000)) have been used extensively. The SUE function has been adapted with MBS and NACH for the bi/tri-criteria control problems. The approaches proposed for MBS and NACH using the SUE function are referred to as MBS-SUE and NACH-SUE respectively. The MBS-SUE approach searches for the best MBS to attain maximum weighted value, and the NACH-SUE approach explores the best batch processing point among arrivals using near-future arrival information.

1.4 Organization of the dissertation

The dissertation is organized into six chapters. Chapter I introduces the research problems. In the next chapter, past research studies relevant to dynamic control of batch process systems are reviewed. In Chapter III, the SUE function is introduced and the procedures to derive it for tardiness only, earliness only, and both earliness and tardiness are presented. Chapter IV discusses how to apply the SUE function to existing approaches to solve bi-criteria (cycle time and tardiness) problem and the simulation results for benchmark strategies such as NACH-SUE, MBS-SUE, no idle and full batch are analyzed. Chapter V demonstrates benchmark approaches to solve tri- criteria problem as an extension of the models developed in Chapter IV and then discusses the results from the benchmark approaches. Chapter VI discusses contributions of this dissertation and suggests topics for additional research in the future.

CHAPTER II

BACKGROUND AND LITERATURE REVIEW

While only scant literature exists on using utility value to solve strategic decision problems in dynamic control of batch processing systems, there is considerable analysis of their performance using metrics such as cycle time, tardiness, earliness, and multi-factors. This dissertation groups the literature into a cycle time-related approach, a due date-related approach, and a multiple criteria batch process control problem categorized by a cycle time and due date-related approach and an earliness and tardiness-related approach. Mathirajan and Sivakumar (2006a), who reviewed the literature on batch process control problems, have grouped papers into stochastic and deterministic problems. Based on the nature of the product flow and availability of future information, Cerekci and Banerjee (2010) have created three subgroups of problems based on availability of arrival information from an upstream process: no future arrival information, full knowledge on future arrivals, and near-future arrival information. On the other hand, this dissertation represents the subgroup of the literature by solution methodology: mathematical programming, heuristic and simulation.

2.1 Single criterion batch process control problem

2.1.1 Cycle time-related approach

Table 2.1 groups the existing literature according to the solutions described.

Table 2.1. List of literature on cycle time-related approach

Solution Methodology \ Availability of data	**Deterministic**	**Stochastic**
Mathematical Programming	Chandru *et al.* (1993b), Hochbaum and Landy (1997), Dobson and Nambimadom (2001), Azizoglu and Webster (2001), Dupont and Dhaenens-Flipo (2002)	Chandru *et al*. (1993a), Duenyas and Neale (1997), Avramidis *et al*. (1998), Neale and Duenyas (2000), Lee and Uzsoy (1999), Liu and Yu (2000)
Heuristic	Ahmadi *et al*. (1992), Uzsoy (1994), Uzsoy and Yaoyu (1997), Kim and Kim (2002)	Bailey(1954), Neuts (1967), Deb and Serfozo (1973), Glassey and Weng (1991), Gurnani *et al*. (1992), Weng and Leachman (1993), Robinson *et al*. (1995), Uzsoy (1995), Fowler *et al*. (1992), (2000), Sung *et al*. (2002), Van Der Zee *et al*. (1997), (2001), Van Der Zee (2002), (2007), Cigolini *et al*. (2002), Cheraghi *et al*. (2003)
Simulation	No report	Akcali *et al*. (2000), Solomon *et al*. (2002)

2.1.1.1 Deterministic problem with cycle time-related objective

The deterministic problem assumes the availability of full data. Therefore the solution focuses on batch formation and ordering of batches.

Chandru *et al*. (1993a) has solved the problem when products can be categorized with the same process time where minimization of total completion time can be obtained in polynomial time. In a previous research, Chandru *et al*. (1993b) tried to solve the problem of minimizing total completion time for compatible product types using a branch and bound algorithm that eliminated a significant percentage of the batching alternatives. However, it requires a heuristic algorithm to solve problems that are too complex. Hochbaum and Landy (1997) have extended Chandru *et al*.'s approach by using an exact pseudopolynomial algorithm and a polynomial approximation algorithm for multiple products and machines. Dobson and Nambimadom (2001) have utilized integer programming and proposed an iterative batching sequencing solution procedure which can obtain a local optimum. Consequently, they developed a polynomial time optimal solution procedure for a special case and discussed the solution qualities compared to the heuristic's solution. Azizoglu and Webster (2001) have solved the problem of incompatible types and non-identical sizes of products with the use of a branch and bound procedure for 25 products. The issues of non-identical product sizes and a small quantity of product were investigated by Dupont and Dhaenens-Flipo (2002) as well. To minimize makespan, a branch and bound procedure was used to find the optimal solution to spending less computational time than previous approaches.

Other researchers have taken a heuristic approach to solving complexity. For example, Ahmadi *et al*. (1992) have studied multi-station systems with compatible product types, constant batch process times and a total completion time. They developed a polynomial procedure as well as a heuristic algorithm and established an upper bound on the worst-case performance ratio of the heuristic for the NP-hard problem. Uzsoy (1994) has solved the NP-hard problem for different sizes of batches and different machine capacities by minimizing total completion time and makespan. Uzsoy and Yaoyu (1997) have solved the problem with identical product sizes compared to the research of Azizoglu and Webster (2001) on non-identical product sizes. Uzsoy and Yaoyu have also addressed priority weights assigned to products and a total weighted completion time criteria by employing several heuristic approaches and a composite heuristic with an embedded local search. Kim and Kim (2002) have demonstrated the efficiency of a genetic algorithm (GA) compared to Ahmadi *et al*. (1992).

2.1.1.2 Stochastic problem with cycle time-related objective

In most cases, the nature of the batch process control problem is more likely to be stochastic. According to solution methodology, such problems can be categorized into three groups: mathematical programming, heuristic, and simulation.

For the first group, Chandru *et al*. (1993a) have solved the problem for minimizing total completion time on a single batch process machine for different jobs by proposing a dynamic programming algorithm of polynomial time complexity. Duenyas and Neale (1997) have provided an optimal control limit method for a single batch processor for two types of commodities. Their dynamic programming algorithm and heuristic control policies solve for a larger number of commodity types. Neale and Duenyas (2000) have discussed a case of compatible product types where the distributions of arrivals for each commodity differ and the commodities of different types can be batched. In cases where near-future arrival information is assumed to be available to the decision-maker, a decision point is chosen at points when the batch processor becomes idle, or an arrival occurs while the batch processor is idle. Neale and Duenyas (2000) have proposed a semi-Markov decision approach for two product types that causes increasing problem space non-polynomially by the number of product types.

Deb and Serfozo (1973) have utilized a dynamic programming algorithm to select the minimum batch size (MBS) in order to minimize the discounted cost.

Avramidis *et al*. (1998) have extended Deb and Serfozo's approach. They have proposed an optimal batch control policy that minimizes the expected average number of products in queue. Considering the compatibility of product types, Lee and Uzsoy (1999) have developed polynomial approach for special cases, such as agreeable arrival and process times, and two distinct arrival times. They have also proposed the heuristic approaches for the general problem. Liu and Yu (2000) have solved the problem which has criteria for compatible product types and makespan. Since the problem is NP-hard for a fixed number of static arrivals, they have suggested a greedy heuristic approach with an approximation level of two.

The second group includes work by Mathirajan and Sivakumar (2006b) who have developed three categories: simple (constructive) heuristic; meta-heuristic, which they have further categorized by genetic algorithm, simulated annealing and neural network; and a mathematical programming-based heuristic. Bailey (1954) was the first to research a bulk service queueing system for single arrival/single server system with Poisson process and service in batches. The batch processing policy, Minimum Batch Size (MBS), has become one of the most effective methods for batch processing. Neuts (1967) has focused on optimizing a batch service queue with Poisson arrivals of a single commodity using the MBS rule, where a batch is processed when the number of commodities in the queue exceeds the predetermined MBS value. Deb and Serfozo (1973) have developed a dynamic programming method to optimize MBS to minimize expected cost, while Glassey and Weng (1991) have provided the first look-ahead batch control policy, termed Dynamic Batching Heuristic (DBH), which uses the mean waiting time of the commodities just before a batch processor as the performance measure.

Gurnani *et al*. (1992), who researched the use of control limit policies on two-stage processor systems, have considered a serial batch processor system with serial processors feeding a batch processor. Random failures that occur in a serial processor will change the arrival over time. The authors have suggested a control limit policy to minimize the costs caused by the control of the batch processor, using the control limit from stochastic dynamic programming with a renewal approximation method. Weng and Leachman (1993) have adopted the idea of DBH to develop a Minimum Cost Rate (MCR) policy. MCR uses n future arrival epochs which are dynamically evaluated to find the batching epoch that is expected to minimize the holding cost per time unit.

Fowler *et al*. (1992)'s Next Arrival Control Heuristic (NACH) integrates a rolling horizon method. NACH considers only the next arrival time in order to determine whether it is more efficient to start the batch process at the next arrival time. The decision-making process is repeated once the arrival occurs. Fowler *et al*. (2000) have extended NACH to multiple processors. Robinson *et al*. (1995) have developed the Rolling Horizon Cost Rate (RHCR) heuristic for single batch processing machine; it combines the rolling horizon concept of Fowler *et al*. (1992) and the cost-based objective of Weng and Leachman (1993).

Uzsoy (1995) has provided a time symmetric solution procedure following a full batch policy. The procedure focuses on the makespan of a batch processor with incompatible product types. Sung *et al*. (2002) have presented a dynamic programming approach that has polynomial complexity with the number of products in each group and exponential complexity with the number of groups. Their approach assumes that products can be grouped by a fixed number of different batch process times.

Van Der Zee *et al*. (1997) have incorporated the MCR policy for multiple batch processors in their Dynamic Job Assignment Heuristic (DJAH) which considers the next arrival times of product types and selects the batch process starting point using an approach similar to NACH. Comparable to MCR, DJAH uses a cost rate method to evaluate the effect of batching decisions. Van Der Zee *et al*. (2001) have extended DJAH to multiple parallel batch processors and also have presented a comparable control strategy for compatible product types (Van Der Zee (2007)). Cigolini *et al*. (2002) have created the "Wait No Longer Than Time" (WNLTT) approach. For a certain product type, WNLTT is the maximum time by which another arrival of the product type decreases the total waiting time of all products. A certain WNLTT value of each product type is calculated and the minimum value is selected as the global WNLTT. Cheraghi *et al*. (2003) have developed a GA-based heuristic approach for the problem when batch process times are the same for all product types and the products have due dates, which is a mandatory option, in a schedule.

The third group has not been explored much, since only a few researchers have effectively coupled decision algorithms and simulation package, termed simulation-based scheduling, for scheduling batch processors (Mathirajan and Sivakumar (2006b)). Akcali *et al*. (2000) have proposed an alternative control limit approach for multiple product types. This two-stage approach separates the batch control problem into a loading and a dispatching problem. The loading problem decides whether to start a batch or to wait for future arrivals. There are three diverse threshold approaches for this first stage, all of which result in every product type being chosen for batching or waiting. The authors' second stage, the dispatching problem, chooses the type of product to be batched and processed, and they have developed several priority metrics.

Solomon *et al*. (2002) have developed a new version of NACH, termed NACH-setup, for the multiple product type in a two-stage system in which a batch processor is followed by a serial processor. The serial processor at the downstream process has a setup time that occurs when two consecutive products are from different types. The authors have discussed the influence of downstream setup times on batching decisions.

2.1.2 Due date-related approach

Similar to the cycle time-related problem, due date-related problems also can be categorized in three groups: mathematical programming, heuristic and simulation. Table 2.2 groups the existing literature for due date-related approaches according to the solutions described.

Table 2.2. List of literature on due date-related approach

Solution Methodology \ Availability of data	Deterministic	Stochastic
Mathematical Programming	Hochbaum and Landy (1994), Mehta and Uzsoy (1998), Cheng *et al*. (2001), Jolai (2005)	Erel and Ghosh (2007)
Heuristic	Balasubramanian, *et al*. (2004), Perez *et al*. (2005)	Li and Lee (1997), Kim *et al*. (2001), Mason *et al*. (2002), Monch *et al*. (2005), Habenicht and Monch (2005), Mathirajan and Sivakumar (2006b), Tangudu and Kurz (2006), Sha *et al*. (2007), Chou and Wang (2008)
Simulation	No report	No report

2.1.2.1 Deterministic problem with due date-related objective

For the first group, Hochbaum and Landy (1994) have introduced the Weighted Tardiness with Batching (WTB) problem, consisting of a batch setup time, n jobs with a processing time, a weight, and a due date. The objective is to find a sequence of batches minimizing the weighted number of tardy jobs. To solve this problem, Hochbaum and Landy have utilized pseudo-polynomial time by a dynamic programming algorithm since the decision version of WTB is NP-complete.

Mehta and Uzsoy (1998) have utilized dynamic programming in scheduling for a single batch processor and multiple product types. They have solved the NP-hard problem to minimize total tardiness. They have proposed a dynamic programming approach with polynomial complexity for the number of products. To find the solution with ease, a heuristic batch prioritization approach, or the Batch Apparent Tardiness

Cost (BATC), considers the batch and utilizes the Apparent Tardiness Cost (ATC) rule proposed by Vepsalainen and Morton (1987). Using the BATC rule obtains the BATC index; batches with this index can then be sequenced by their priority indices.

Cheng *et al*. (2001) have examined the unbounded version of the scheduling problem which has jobs with agreeable processing times and deadlines. For NP-completeness, they have presented polynomial time algorithms to solve the following: agreeable release dates and processing times; agreeable release dates and deadlines; distinct processing times or distinct deadlines; and a fixed number of distinct release dates.

Jolai (2005) has utilized a dynamic programming approach to minimize the number of tardy jobs for incompatible product types. Although the number of product types causes complexity, Jolai has analyzed a polynomial solution for a special case where the same types of products have common due-dates.

For the second group, heuristic approaches, Balasubramanian, *et al*. (2004) have solved the problem with a parallel batch processor for total weighted tardiness criteria using a three-stage decomposition algorithm. The first algorithm allows three steps to be taken: products are assigned to batches; batches are allocated to processors; and the order of the batches is decided for each processor. The second algorithm allows three more steps: products are assigned to processors; batches are set by the assigned products for each processor; and the order of batches is decided for each processor. The ordering rule for each product follows the ATC rule and the batches are set following this rule. For the third algorithm, BATC indexing is utilized to order the batch. In addition to the previous rule, GA is used to assign batches and products to the processors in the first and second algorithms.

Perez *et al*. (2005) have experimented with a two-stage framework using combined heuristic approaches for batching and sequencing. The best solution is obtained by using the ATC rule for assigning products to batches and the BATC rule for deciding the initial sequence of the batches.

2.1.2.2 Stochastic problem with due date-related objective

Similar to the cycle time-related approach, the nature of the batch process control problem is more likely to be stochastic. Due date-related problems also can be categorized into three groups: mathematical programming; heuristic; and simulation.
For the first group, Erel and Ghosh (2007) have presented a pseudo-polynomial dynamic program and fully-polynomial approximation scheme to minimize the weighted number of tardy jobs for a single machine and the uniform distribution of due dates within a family.

For the second group, Li and Lee (1997) have focused on minimizing maximum tardiness on a single burn-in oven for compatible products. They have proved the NP-hard complexity of the problem, and proposed a dynamic programming algorithm for agreeable ready times and due dates.

Kim *et al*. (2001) have provided the modified DBH strategy developed by Glassey and Weng (1991) to minimize total tardiness. According to the new control method, Modified Dynamic Batching Heuristic (MDBH), product types are prioritized based on the average due date slack waiting time of the products in queue. From the highest priority product type, two decision alternatives which are whether to wait for next arrival or start the batching at current time are compared. The total weighted waiting times that are affected by these alternatives are decided using the inverse of due date slacks as product weights. When a start decision is made, the batch process starts with type of product. On the other hand if all types of product return a wait decision, the decision-making phase is delayed to the next arrival point.

Extending Dynamic Batching Dispatching Heuristic (DBDH), developed by Mason *et al*. (2002), Monch *et al*. (2005) have proposed a three time-window-based priority indexing method. BATC-I and BATC-II, demonstrate effective performances compared to alternative heuristics. Hochbaum and Landy (1997) have also discussed the decision theory in prioritization of batches. According to this approach, total weighted tardiness of alternative is obtained in the time window and the decision alternative with the minimum value is selected. This approach is beneficial in the sense that the decision process accounts for the effect of a batching decision on other product types.

Habenicht and Monch (2005) have attached a time window-based batch composition to the prioritization approach presented by Mason *et al*. (2002). According to the DBDH, all possible batches in a time window are selected and prioritized for each product type. Accordingly, the final decision is made by the priority of the alternative batch compositions.

Mathirajan and Sivakumar (2006b) have discussed a heuristic algorithm with three step for scheduling parallel non-identical batch processors with non-identical product sizes. In the first step, algorithms choose the processor that will be scheduled next from the availability times of the machines. In the second step, the product type loading to the processor is chosen using priority operated by the processing times and the due dates of the product types. In the third step, a batch to the full extent from the available product type is chosen with priority rules. Then the availability time of the processor is changed to the completing time of the chosen batch. These three steps replicate until all products are scheduled.

Tangudu and Kurz (2006) have studied the problem which has incompatible product types and total tardiness criteria. They have provided a branch and bound procedure with better complexity than complete enumeration.

Cha *et al*. (2007) have proposed a due date-related batching rule, called look-ahead batching rule (LBCR), a combination of Cost Rate (CR) for dispatching rule and NACH for batching dispatching rule, in order to increase the rate of on-time delivering and decrease waiting time for jobs. This approach elevates delivery rates and reduces average tardiness.

Chou and Wang (2008) have provided a mathematical programming approach and two hybrid heuristics, a rule-based algorithm and a GA, to consider the problem of a single batch processor with job release times, non-identical job sizes, different due dates, and weights to minimize the total tardiness. For a given job sequence, a dynamic programming (DP) algorithm is incorporated to find an optimal batching solution.

2.2 Multiple criteria batch process control problem

Generally, a single criterion, such as cycle time, tardiness, WIP, or makespan, is used to solve batch process control problems. However, in practice many other factors should be included even though they are difficult to determine due to differences of metrics, the trade-off in relationships, etc. This makes the formulation and solution much more complex, and as a result, there is a scarcity of literature available on the use of multiple criteria.

Table 2.3 groups the existing literature for multiple criteria approach which can be categorized by cycle time and due date, and earliness and tardiness according to the solution methodology.

Table 2.3. List of literature on approach for multiple criteria

Considered criteria / Solution Methodology	Cycle time and Due date	Earliness and Tardiness
Mathematical Programming	No report	Wu and Wang (1999)
Heuristic (Genetic)	Monch *et al*. (2005) , Reichelt and Monch (2006), Mason *et al.* (2007)	Gupta and Sivakumar (2007)
Heuristic (Pareto optimal)	Ganesan *et al*. (2004) , Gupta and Sivakumar (2005), Cerecki and Benerjee (2010)	Monch *et al*. (2006), Jeong and Kim (2008)

2.2.1 Cycle time and due date-related approach

Considering cycle time/due date criteria, Monch *et al*. (2005) have provided two different decomposition approaches for the given NP-hard problem in order to minimize total weighted tardiness on parallel machines with incompatible families and jobs with unequal ready times. The first approach fixes the batches, assigns them to the machines using GA, and sequences the batches on each machine. The second approach assigns jobs to machines using a GA, figures the batches for each individual machine for the assigned jobs, and sequences these batches.

Reichelt and Monch (2006) have focused on minimizing makespan and total weighted tardiness on multiple batch processors. Their approach follows the three-stage (batching, assignment and sequencing) algorithm developed by Monch *et al*. (2005). The adaptation occurs in the batch assignment stage (GA-based method), Non-dominated Sorting Genetic Algorithm II (NSGA-II) is utilized to find the Pareto-optimal solutions and a local search method is utilized to improve the Pareto-optimal solutions.

Mason *et al.* (2007) has used NSGA-II to improve on time delivery, decrease cycle time variation, and decrease violation of the timer to minimize recirculation.

Ganesan *et al*. (2004) have proposed scheduling for the batch processors to minimize mean cycle time and maximum tardiness. According to this research, each decision is made within the short-term future and the outcomes with respect to the criteria are evaluated. It shows Pareto-optimal decision to be obtained and provided to the decision-maker as the Pareto-optimal boundary.

For the NP-hard problem of n independent jobs with due dates and sequence-dependent setup times, Gupta and Sivakumar (2005) have utilized a Pareto-optimal approach to minimize average cycle time, average tardiness, and to maximize machine utilization. First, they used a discrete event simulation approach and then compromised programming approach at each decision point in simulated time.

2.2.2 Earliness and tardiness related approach

Due to the complexity of the problem for multiple criteria, there is limited use of mathematical programming approach to solve the problem. However, the problem for earliness and tardiness is comparatively simple to solve with mathematical programming approach. Wu and Wang (1999) have considered the problem for optimal due dates and optimal sequence to a set of jobs on a single machine. Five lemmas and a polynomial-time algorithm minimize the earliness and tardiness penalties and additional penalties such as due date penalties and completion time penalties.

Solving the earliness and tardiness problem is important in Just-In-Time (JIT) systems. In JIT systems, completion of jobs before due date affects in-storage cost, while completion of jobs after due dates affects contract penalties, loss of good will, etc.

Monch *et al*. (2006) have proposed several two-phase heuristic approaches based on GA and dominance properties to minimize the sum of the deviation from due date for earliness and tardiness. The first phase uses the condition of no-maximum allowable tardiness constraint, and the second phase changes the schedule to meet maximum allowable tardiness constraint.

Gupta and Sivakumar (2007) have studied how to minimize earliness and tardiness on a batch processor. A look-ahead batching method evaluates different batch scenarios and compromise programming is used to find the Pareto-optimal boundary.

Jeong and Kim (2008) have considered *n* jobs with different release times, due dates, and space limits on parallel machines. Their heuristic approach consists of job selection, job assignment and sequencing, and solution improvement. This three-module heuristic has been compared to GA, hybrid GA, and Tabu Search (TS).

While various research studies to solve single or bi-criteria problem have been discussed in this chapter, there is very limited amount of literature which consider the weight of each product type that changes over time. As discussed in Chapter I, in a long production cycle time system the utility value of lots can vary for diverse factors, such as contractual penalties, change of price for product, loss of customer goodwill, surplus of lots, etc. Among the time-dependent factors, due date and storage cost, are particularly critical, since utility value can significantly vary in response to the penalties that may be imposed for missing the due date deadline. Obtaining the utility evaluation function which reflects the accurate value at each epoch is more desirable from a business decision making perspective. Therefore SUE function is developed and introduced in the next Chapter. The SUE functions are subsequently applied to existing batch process control methods to overcome some of the limitation found in existing literature.

CHAPTER III

STOCHASTIC UTILITY EVALUATION FUNCTION APPROACH

In practice, due date and storage cost are two important factors that have considerable impact on utility value. A utility evaluation function can be approximately derived from existing business information on these factors that affects tardiness and storage cost that affects earliness.

Clark (1990) has identified the time-utility function by considering the very simple case of time-utility function which is due date-oriented.

Figure 3.1, representing the constant time-utility functions

$$f_k(t) = U_k, \quad \forall t$$

shows that utilities are constant over time. Park and Banerjee (2010) have used three utility evaluation functions and applied these to existing models - MBS-U and DBH-U. Figure 3.2 shows that a hard deadline utility function has a utility value of 1 before due date, otherwise a value of 0. Figure 3.3 demonstrates a step time utility function which has different values on both sides of the due date. Figure 3.4 shows a linear time utility function with a linear slope over time.

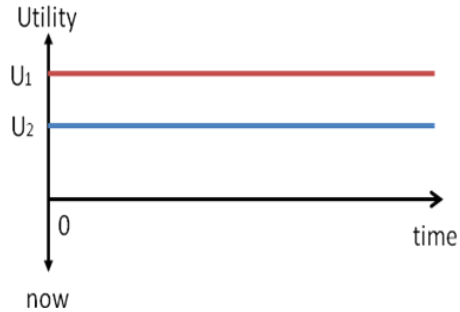


Fig. 3.1. Constant time utility function

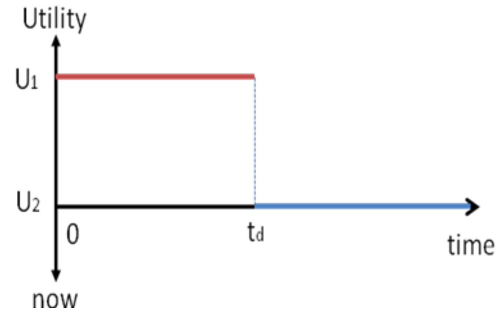


Fig. 3.2. Hard deadline time utility function

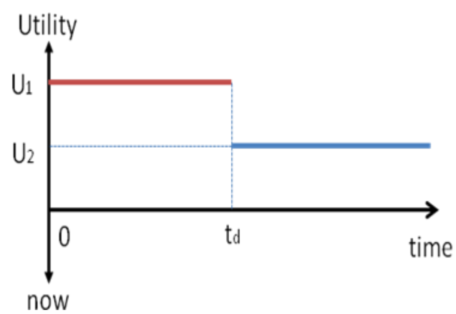


Fig. 3.3. Step time utility function

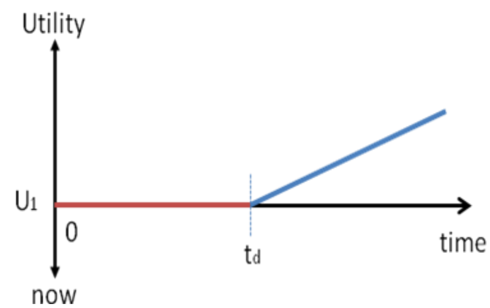


Fig. 3.4. Linear time utility function

For ease of explanation, they make the following assumptions for utility evaluation function:

i) Utility evaluation function is a linear time utility model.

ii) The due date used in time utility function is "current time", not "expected time to finish". In other words, use the current time to obtain utility value at the point when current time is not past the due date, but expected time to finish the job is past the due date. In other words, use the current time to obtain utility value when at the point that current time is not past the due date, but expected time to finish the job is past the due date.

Their model, however, was preliminary and limited since they assumed linear utility evaluation functions. According to assumptions made for utility function, the result can vary substantially and be trivial. They did not consider due date prior to occurrence. For example, if tardiness is not considered before due date in the bi-criteria problem (cycle time and tardiness), the algorithm focuses on reducing cycle time. However, as the time approaches due date, tardiness becomes more important; thus, to reflect its importance before the due date, the utility function must have a value before due date. Finally, although they have used a stochastic process for the interarrival time, information from the distribution, such as the likelihood estimator, was not used for decision making. A stochastic utility evaluation function has been developed in this research in order to overcome these limitations.

3.1 Introduction of the stochastic utility evaluation (SUE) function

Most of the literature has used stochastic process for arrivals such as exponential distribution (Cerekci and Benerjee (2010), Fowler, *et al*. (1992), Van Der Zee, *et al*. (2001), to cite a few), and for solving the bi-criteria problem, which is often highly subjective weight for tardiness has been specified by decision maker. However, in a stochastic process, the probability function which indicates the values of the relationship between the two variables, a random variable and independent variable, can be derived. Also, the probability function introduces the variable indicating the values within the range of a random variable and the probability as the dependent variable. Therefore, when the weight for tardiness changing over time needs to be considered, the value from the probability function can be used as the weight for tardiness. The value from a probability function can be considered as more objective than the value obtained by a decision maker. Even though the value from a decision maker is subjective, in the existing approach for solving the bi-criteria problem the weight for tardiness is still decided by decision maker, and the weight is fixed over time in their approaches. Based on the weight from a probability function, this research introduces a Stochastic Evaluation Utility (SUE) function that captures the weight for a factor that changes over time.

The following notations are used here for the SUE function:

$N_j = number\ of\ order\ for\ product\ j$

$D_j = Due\ date\ for\ product\ j$

$C_{tj} = Completed\ jobs\ for\ product\ j\ at\ time\ t$

$a_j = Number\ of\ remaining\ orders\ for\ product\ j\ at\ time\ t$

$W_j(t) = Weight\ function\ for\ product\ j\ at\ time\ t$

$F_j(t, a_j) = Probability\ function\ for\ product\ j\ at\ time\ t$

$given\ number\ of\ remaining\ orders\ for\ product\ j$

The SUE function for batch process control problem can be defined as follows:

$$U_j(t) = W_j(t) = f\left(F_j(t, a_j), D_j, N_j, C_{tj}\right)$$

The objective of SUE function is to find the optimal weight for a specified factor. Parameters and variables from the problem, (the percentage jobs that can be completed by due date), are used in SUE function. The SUE function $U_j(t)$ combines the probability to complete jobs by due date using a stochastic approach, and other deterministic parameters: due date, number of orders, completed jobs and remaining orders.

For example, assume that arrival rate of a specific job type follows exponential distribution, due date is time T and number of orders is *n*. Two cases are possible. The first case estimates the probability to finish remaining jobs by due date at a decision epoch. If the probability is low, it means that there will not be enough arrivals of lots to complete all the jobs by due date. Thus the weight for tardiness should be high to complete the jobs by due date. The second case finds the ratio of remaining orders and number of possible jobs to complete them. If the ratio is high, less number of lots than orders will arrive at the batch processor by due date. Thus the SUE function can be obtained as in the first case.

Earliest Due-date (EDD) is a common strategy to prioritize different batch arrangements. When there is an available product in queue, a batch is processed according to EDD strategy. The batch which has a minimum average due-date is chosen to be processed on the machine. However, EDD strategy has a vital problem when due-date for each product is very similar and the number of remaining order for each product has a large difference (see Figure 3.5).

Due date of product 1 is close to due date of product 2 and the number of products in queue is the same (=5). However, at decision epoch, the number of remaining orders is significantly different for each product. If EDD strategy is used to choose an alternative, the decision is that the batch of product 1 is processed. However, even though due date of product 2 is later than product 1, the batch of product 2 needs to be processed since product 1 still has a chance to be on time (no tardiness) for the remaining time until due date. On the other hand, if product 2 (which has a large number of remaining orders) is not processed at decision epoch, the possibility to be on time becomes lower and tardiness becomes larger.

From this point of view, a SUE function strategy is more useful than EDD strategy since the SUE function considers due date, number of remaining orders and remaining time until due date.

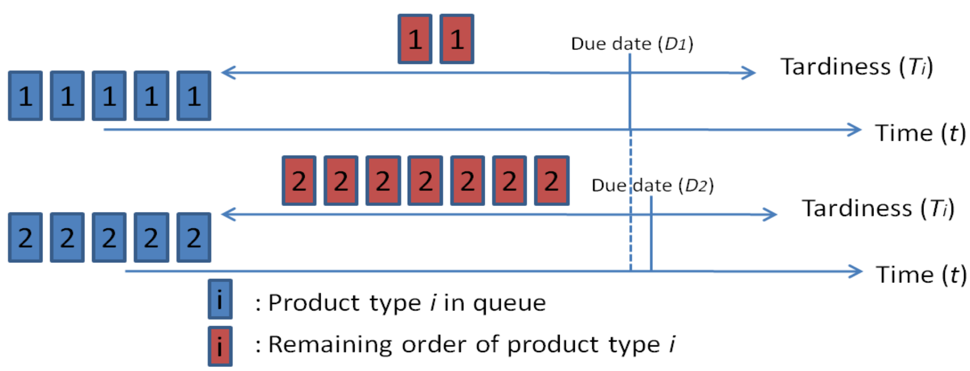


Fig. 3.5. Example for EDD strategy for slightly different due dates of two types of products and significantly different number of remaining orders of two types of products

3.2 SUE function for tardiness

Researchers have proposed various approaches and algorithms considering cycle time, tardiness and both cycle time and tardiness for solving the batch process control problem. Among these approaches, solving the bi-criteria objective optimization problem is more difficult than the single criterion objective problem, due to the trade-off between cycle time and tardiness. In order to solve the bi-criteria problem, they have focused on ways to combine the weight for each criterion into a single criterion. However there are limitations to this approach as they do not account for changing weight for each criterion. This research modifies the existing approach using a SUE function to convert a single criterion problem into a bi-criteria problem and solve the bi-criteria problems to reflect the changing weight over time.

Genetic and pareto-optimal approaches have been used to solve bi-criteria objective optimization problems. The latter approach combines multiple objectives into one scalar objective. Pareto optimal approaches can be categorized into weighted aggregation, minimum fractional deviation, global criterion and compromise programming. All of these use weights for all the criteria chosen by the decision-maker. The weight chosen by a decision maker can often lack objectivity. On the other hand, the use of SUE function, which is derived from stochastic information, such as expected estimation, can potentially provide the desired objective weight.

Assume that lots arrive at a batch processor according to an exponential distribution with rate λ, number of order N, and due date D. In order to obtain the SUE function, the probability to finish jobs given remaining time by due date is considered. The probability function $F(\cdot)$ of the random variable X, given number of order N and due date D for arrival distribution at time t for a single product is defined by

$$F(t, a) = 1 - P\{X \ \le a \mid t\}$$

The function obtains the estimated probability that random variable X takes on a value that is less than or equal to number of remaining orders by due date. If a lower probability is estimated, the probability not to complete jobs by due date is higher, which implies that tardiness increases. Therefore, this property provides weights for tardiness at time t when the SUE function is plugged into the cycle time-based approach to solve bi-criteria objective problems.

If there will be enough arrivals to complete jobs by due date, the algorithm for bi-criteria problem needs to focus on minimizing cycle time since the probability of not completing jobs is very low. In this case, the weight for tardiness can be the value of 1 and the algorithm is exactly the same as cycle time based approach. However, as time approaches due date, the probability of not completing jobs increases. Therefore the weight for tardiness increases by the amount of increased probability.

Now assume that lots arrive at a batch processor according to an exponential distribution with rate λ. Figure 3.6 shows a specific example where as time approaches due date (100 time units), the probability to complete jobs by due date decreases.

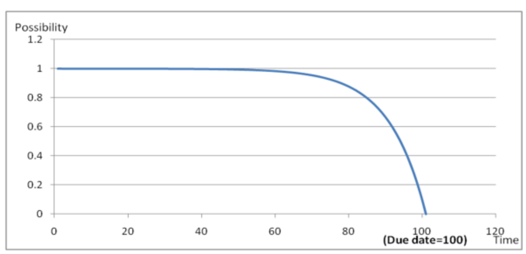


Fig. 3.6. Time-probability function

On the other hand, as time approaches due date, the weight for tardiness increases since tardiness must be considered more than cycle time in order to complete jobs by due date. Figure 3.7 shows a specific instance of the weight change over time and assumes the formula

$$W(t) = 1, \quad where\ F(t,a) = 1$$

$$W(t) = 2 - F(t,a), \quad where\ F(t,a) < 1$$

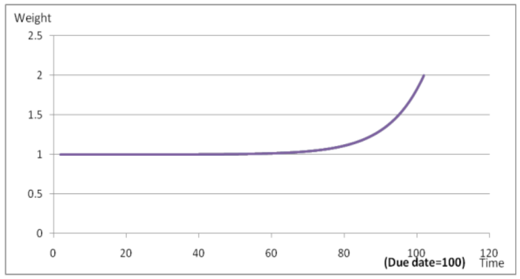


Fig. 3.7. Time-weight function for tardiness

The applicable tardiness value can be plugged into existing approaches for minimizing cycle time in order to solve the bi-criteria objective (cycle time and tardiness) problem.

3.3 SUE function for earliness and tardiness

The SUE function for earliness can also be derived from following the procedure for tardiness described above; however, earliness occurs far from due date.

When earliness is considered in the probability function, JIT scheduling is important. In order to acquire the JIT schedule, the minimum period when number of arrival is the same as number of orders is set up.

After due date, earliness does not need to be considered since just after completing jobs, products depart from the current system to the next. Thus, in this case, the weight for earliness is the value of 1, which is the base value. On the other hand, the weight for the earliness is increasing as time is further from due date since time in storage is increasing.

In practice, the tardiness cost such as contractual penalty and earliness cost such as storage cost can be obtained. Therefore the ratios of the comparative weights for earliness and tardiness are used to get the probability and SUE function for the earliness and tardiness.

Now assume that lots arrive at a batch processor according to an exponential distribution with rate λ. As time approaches due date, the probability to complete jobs by due date decreases (see Figure 3.6). On the other hand, as time approaches due date, the weight for earliness decreases as a result of a decrease in storage cost. Figure 3.8 shows an example of the weight change of earliness over time and assumes the formula (the costs for tardiness include contractual penalty and loss of consumer's good will; the cost for earliness includes storage cost).

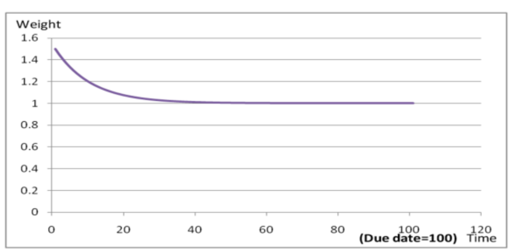


Fig. 3.8. Time-weight function for earliness

$$r = \frac{cost\ for\ earliness}{cost\ for\ tardiness}$$

$$W(t) = 1, \quad where\ F(t, a) = 0$$

$$W(t) = 1 + r * F(D - t, a), \qquad where\ 1 > F(t, a) > 0$$

$$W(t) = 1 + r,\ \ where\ F(t, a) = 1$$

Figure 3.9 illustrates a SUE function to solve the tri-criteria objective problem and uses the formula

$$W_{ET}(t) = W_E(t) + W_T(t) - 1$$; where

$$W_E(t) = Weight\ for\ earliness$$

$$W_T(t) = Weight\ for\ tardiness$$

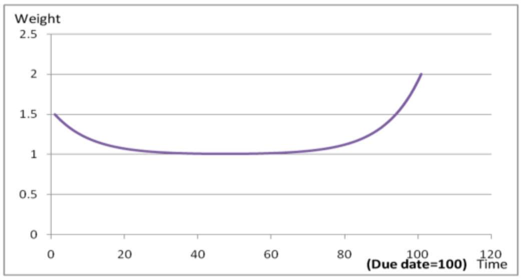


Fig. 3.9. Time-weight function for earliness/tardiness

As mentioned earlier, there is limited research for solving the tri-criteria objective problem including cycle time, earliness and tardiness. However, the value from a SUE function (for both earliness and tardiness) can be plugged into existing approaches which minimize cycle time only.

3.4 Contribution of the chapter

The contributions of the research provided in this chapter are the follow:

i) Most dynamic control methodologies for batch process systems are using static weight for each product type. However, in the more than two criteria problem such as cycle time and tardiness, cycle time and earliness/tardiness the weight for each criteria of product type changes over time. In this Chapter, the main contribution is that a SUE function is introduced to provide a decision-maker with more information about the conditions of the existing batch process control program.

ii) Utility evaluation function used in most research is assumed subjectively as constant, linear, step function, etc. However, the utility evaluation (weight) given by decision maker has the potential for being inaccurate leading to the results not being objective and robust. This chapter explores how stochastic utility function using stochastic information can be derived. This supports the objectiveness for generating a weight for each product type at each decision epoch.

iii) The weight for product type for all criteria can be derived from combining the SUE functions for each criterion. The relationship between SUE function of each criterion such as the ratio of storage cost and late penalty (earliness vs. tardiness) supports to generate the combined SUE function. This chapter introduces a SUE function for earliness and tardiness using ratio of two criteria based on costs.

CHAPTER IV

APPLICATION OF SUE FUNCTION TO BATCH PROCESS CONTROL PROBLEM: CYCLE TIME AND DUE DATE RELATED APPROACH

This chapter shows how to apply the SUE function to existing models for bi-criteria objective problems.

Using the SUE function for tardiness, a similar procedure can be applied to the bi-objective approach such as MBS, NACH, Full batch and No idle. The benchmark strategies are described below:

4.1 Modification of the benchmark strategy for bi-criteria problem

4.1.1 MBS-SUE approach for bi-criteria problem

The MBS method starts a batch process when the number of waiting commodities is greater than or equal to the MBS. The model selects the best MBS which optimizes a performance metric (e.g., overall cycle time) of commodities. MBS-SUE is similar, except that it uses a weighted value reflecting the SUE function to determine minimum batch size instead of time-based value, delay. Using the SUE function, the weighted value remains constant (=1) when a job is expected on time (i.e. the SUE function has the value of "1"), since the weights for commodities do not change. Once a job is expected to be late (i.e. the weight for product has the changed value from the SUE function), the results of MBS-SUE will vary with the stochastic information of arrival such as types of arrival distribution and rate, traffic density, etc. Van Der Zee *et al*. (1997) have presented MBSX which is an MBS approach for multiple products and multiple machines. The decision rule is that when more than one type of product has greater than MBS in the queue, the one with the longest waiting time is selected. When there are multiple candidates, the one with the shortest processing time is selected. The MBS-SUE for multiple products is similar to the MBSX approach. When more than one type of product has greater than MBS in the queue, the one with the longest weighted waiting time using the SUE function is selected. When there are multiple candidates, the one with the shortest weighted processing time using the SUE function is selected.

4.1.2 NACH-SUE approach for bi-criteria problem

Fowler *et al*. (2000) proved that NACH is a robust heuristic when forecasting data on future arrivals was utilized. The following notation is used in the NACH approach.

$C_i = Machine\ capacity\ for\ product\ i$

$DD_i = Due\ date\ for\ order\ i$

$N = Number\ of\ product\ type$

$t_0 =$
$Time\ epoch\ when\ machine\ is\ idle\ and\ number\ of\ product\ in\ queue\ is\ positive$

$t_{ij} = Arriving\ epoch\ of\ the\ next\ i^{\text{th}}\ lot\ from\ t_0\ of\ product\ j$

$q_j = Number\ of\ lots\ in\ queue\ of\ product\ j$

$T_j = Processing\ time\ of\ product\ j$

$J = Set\ of\ product\ type$

$DNACH_j = Total\ delay\ when\ product\ j\ is\ loaded$

$SN = Set\ of\ product\ types\ that\ do\ not\ have\ to\ wait\ for\ a\ next\ arrival$

$SY = Set\ of\ product\ types\ that\ have\ to\ wait\ for\ a\ next\ arrival$

$W_j =$
$Total\ delay\ incurred\ by\ the\ other\ products\ when\ product\ j\ is\ being\ processed$

$NACH_j =$
$Total\ waiting\ time\ of\ the\ other\ products\ when\ product\ j\ is\ loaded$

The procedure of NACH approach for single product type is described as below

If the machine is idle,

If full batches are available,

Then batch is processed

Else, evaluate *NACH*,

$NACH = \ [q(t_1 - t_0) - (t_0 + T - t_1)]$

If $NACH < 0$,

Then wait for next arrival.

Else,

Then start and process batch.

Using the weight from the SUE function for tardiness, the gain and loss based on weighted value in the NACH rule is obtained, and the epoch with the most positive gain is chosen as the best epoch.

In order to apply the NACH-SUE for the bi-criteria problem involving cycle time and tardiness, the SUE function for tardiness is applied to the NACH approach.

Therefore the additional loss for NACH-SUE caused by waiting for the future arrival at t_1 is calculated by

$$WArea_1(t) = W_T(t) \times q(t_1 - t_0)$$

This area, which reflects the weighting value from the SUE function for tardiness, represents the total additional loss for the q lots that are in queue at t_0. The gain caused by waiting for the future arrival at t_1 is calculated by:

$$WArea_2(t) = W_T(t) \times \left(t_0 + T_j - t_1\right)$$

Therefore, the net gain is given by

$$WNet(t) = WArea_2(t) - WArea_1(t)$$

Similar to the procedure for a single product case, NACH-SUE for multiple product types for tardiness follows NACH-SUE for tardiness as described below. It is illustrated as a flowchart in Figure 4.1.

If the machine is idle,

If full batches are available,

Then choose a product

$$j^* = arg\ min_{q_i \geq C_j} W_j \ (W_j = T_j \sum_{i \neq j} W_{T_i}(t) \times q_i)$$

and batch is processed.

Here, W_j is the total delay for the other products when the product j is processed. j^* means that among product types, the product j^* has minimum waiting time metric value.

Else, evaluate $NACH_j$ for all j,

$$(NACH_j = \sum_{i=1, i \neq j}^{N} \left[W_{T_i}(t) \times (q_i(t_{1,i} - t_0) - (t_0 + T_j - t_{1,i})) \right] \quad)$$

If $j \in SY$,

then wait *($NACH_j < 0$, for all $j = 1, \ldots, N$).*

Else,

If $j \in SN$ *($NACH_j \geq 0$, for all $j = 1, \ldots, N$),*

Here, *SY* is the set of j which needs to wait for a next arrival.

On the other hand, *SN* is the set of j which does not need to wait for a next arrival.

then choose $j^* = arg\, min_{j \in J}\, W_j$

Else,

$$DNACH_j = W_j + \sum_{i=1}^{N} max\, (0, W_{T_i}(t) \times (t_0 + T_j - t_{1,i})) \quad j \in SN$$

$$DNACH_j = \sum_{i=1}^{N} (W_{T_i}(t) \times q_i(t_{1,i} - t_0)) + W_j + \sum_{i=1}^{N} max\, (0, W_{T_i}(t) \times (t_0 + T_j - t_{1,i}))$$

$j \in SY$

D_j is the total delay when product *j* loaded.

Choose a product $j^* = arg\, min_{j \in J}\, D_j$

If $j^* \in SN$, then batch is processed.

Else, wait.

If the machine is idle and a product j arrives,

Then proceed as indicated by $NACH_j$.

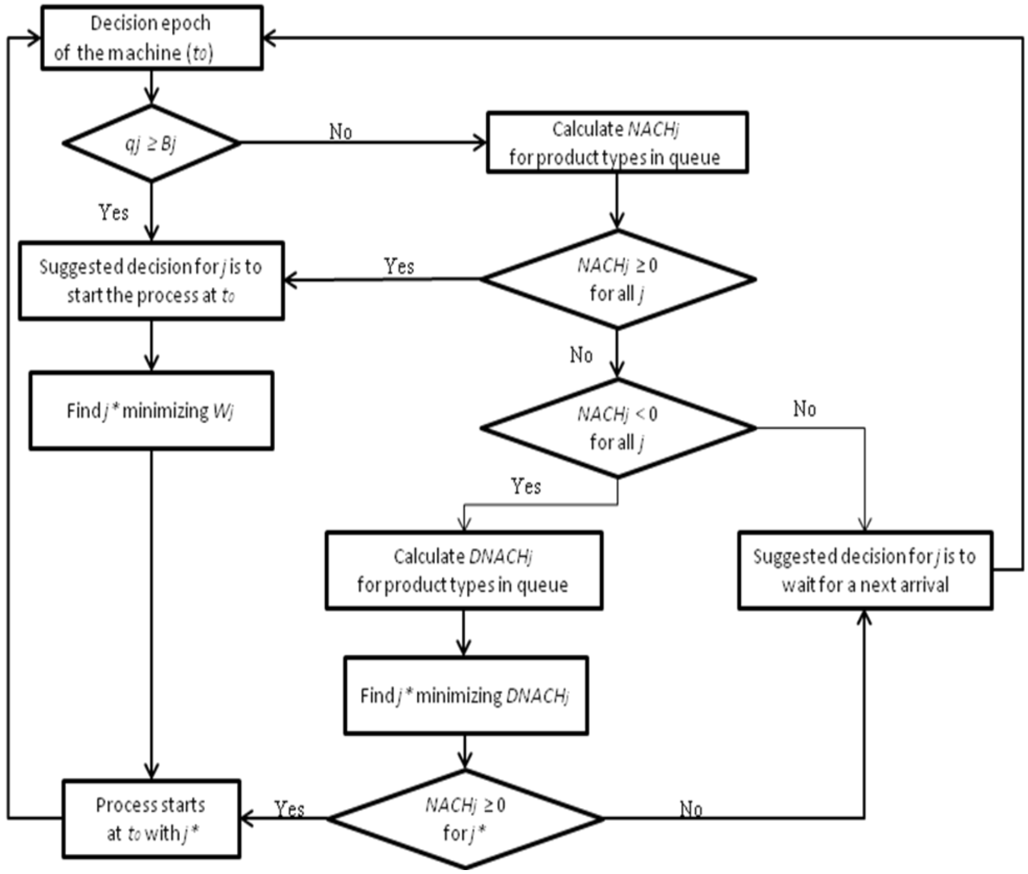


Fig. 4.1. Flow chart of the NACH-SUE algorithm for bi-criteria problem

4.1.3 Full batch approach for bi-criteria problem

At the decision point t_0, if only one available full batch remains in queue, the batch proceeds with the full batch. When there is more than one type of products with full batch in the queue, the type with the longest weighted waiting time using SUE function for tardiness is selected. When there is more than one nominee, the one with the shortest weighted processing time using the SUE function for tardiness is selected.

4.1.4 No idle approach for bi-criteria problem

The purpose of this policy is to keep a processor operating as long as there are available products in the queue. At the decision epoch t_0, if more than one available full batch is available, the no-idling policy is the same as the full batch policy. On the other hand, if there are only partial batches, the one with the longest weighted waiting time using the SUE function for tardiness is selected. As with the full batch policy, when there is more than one nominee, the one with the shortest weighted processing time is selected.

4.2 Simulation results for bi-criteria problem

The performance of modification of the benchmark strategy is experimented under the following conditions. In order to satisfy a reasonable utilization level and steady state queue length, the value of arrival distribution, machine capacity, processing time, due date and number of orders have been chosen (see Table 4.1). Each of the control strategies is tested for each scenario.

A combination of the settings for simulation are:

i) Control strategy: NACH-SUE, MBS-SUE, Full batch, No idle

ii) Simulation run length: 100,000 time units

iii) Number of replication: 10 times

iv) Warm-up period: 5,000 time units

Table 4.1. Configuration of the simulation for bi-criteria problem

No.	Factor	Setting		
1	Number of Products (NP)	2		
	Number of Products (NP)	5		
2	Product Mix (PM)	Equal(E)	2 products	(0.5,0.5)
	Product Mix (PM)	Equal(E)	5 products	(0.2,0.2,0.2,0.2,0.2)
	Product Mix (PM)	Different(D)	2 products	(0.2,0.8)
	Product Mix (PM)	Different(D)	5 products	(0.1,0.1,0.1,0.35,0.35)
3	Machine Capacity by Product (MC)	Equal(E)	2 products	(5,5)
	Machine Capacity by Product (MC)	Equal(E)	5 products	(5,5,5,5,5)
	Machine Capacity by Product (MC)	Different(D)	2 products	(3,7)
	Machine Capacity by Product (MC)	Different(D)	5 products	(3,4,5,6,7)
4	Processing Time by Product (PT)	Equal(E)	2 products	(25,25)
	Processing Time by Product (PT)	Equal(E)	5 products	(25,25,25,25,25)
	Processing Time by Product (PT)	Different(D)	2 products	(10,40)
	Processing Time by Product (PT)	Different(D)	5 products	(10,20,25,30,40)
5	Traffic Intensity (TI)	0.2		
	Traffic Intensity (TI)	0.5		
	Traffic Intensity (TI)	0.8		

Chaudhry and Templeton (1983) have presented the batch traffic intensity (ρ) as the mean arrival rate of each products divided by the maximum batch processing rate when machine is operating at maximum capacity.

The equation for traffic intensity is

$$\lambda_j = \rho / \sum_{j=1}^{N} \frac{P_j T_j}{B_j}$$

where

$\lambda_j = \text{Mean arrival rate for product } j$

$\rho = \text{Batch processor traffic intensity}$

$P_j = \text{Product mix}$

$T_j = \ Batch\ process\ time$

$B_j = \ Batch\ processor\ capacity\ for\ product\ j$

In order to satisfy a reasonable utilization level and steady state queue length, the value of number of order and due date have been chosen for each scenario as follow:

$$N_j = \ S/\rho \times \sum_{j=1}^{N} \frac{P_j B_j}{T_j}$$

where

S = Standard number of order when all factors (product mix, machine capacity, processing time) have equal values

$D_j = \lambda_j \ \times N_j$

In order to create all the settings of simulation scenario, the experiment of control strategies occurring on the set-ups' compilation provide 48 (2x24) scenarios. Each scenario is simulated with each of the control strategies. Along with a run-time of 100,000 time units, a warm up time of 5,000 time units and 10 replications of every scenario are set up. A Pentium dual core 3.20 GHz processor and 2 GB RAM is used for the scenario and Matlab 7.5 is used for the simulation code.

The mean cycle time and tardiness of the replications are averaged over different settings of the product, machine and process characteristics to present the performance of each strategy and performance improvement over static strategy for different settings. A paired-*t* test (95% confidence interval) is used to check the statistical validity of the performance improvements obtained by NACH-SUE, compared to the benchmark strategies. When there is not a significant difference, the performance improvement has a value of 0.

This chapter describes the bi-criteria performance (cycle time and tardiness) of NACH-SUE in comparison with the three benchmark strategies. Tables 4.2, 4.3 and 4.4 provide a summary of the simulation outcomes. The results in the tables are averaged over different settings of the product, machine and process characteristics. The overall performance comparison in Table 4.2 presents that the best performing rule is NACH-SUE. Overall performance improvements obtained by NACH-SUE are 57.43% for cycle time and 39.52% for tardiness, 71.14% for cycle time and 54.58% for tardiness, and 21.58% for cycle time and 40.21% for tardiness when compared to No idle, Full batch and MBS-SUE, respectively (see Table 4.3). This shows that the best strategy which has the most performance improvement is NACH-SUE with respect to No-idle, followed by full batch and MBS-SUE. The closest performing approach to NACH-SUE is MBS-SUE since it is the only benchmark that appraises decision options in collaboration with the effects on all product types. On the other hand, no idle rule and full batch rule performs poorly since no idle rule does not allow waiting for next arrival and full batch rule is necessary to wait for next arrival until making full batch. Table 4.4 presents the performance improvements when SUE function is used in the MBS and NACH strategies. Dynamic control strategy of utility value which is changing over time has significant performance improvement over static control strategy where utility value is fixed at all times.

Table 4.2. Summary of the simulation results for bi-criteria problem

		No idle		Full batch		MBS-SUE		NACH-SUE	
No.	Average at:	cycle time	tardiness	cycle time	tardiness	cycle time	tardiness	cycle time	tardiness
1	Number of products=2	53.49542	259.15	117.7683	291.1521	48.75083	260.1429	41.7425	197.8458
2	Number of products=5	175.4967	446.7838	222.8158	495.5096	76.29125	454.3158	56.55208	234.3408
3	Traffic intensity=0.2	44.1475	290.5481	273.4775	379.5731	44.145	302.8281	43.45	206.785
4	Traffic intensity=0.5	86.14438	423.1981	133.4056	441.5694	65.88	452.0981	56.235	219.2575
5	Traffic intensity=0.8	224.0007	357.4207	104.4347	371.5607	79.29867	327.1353	47.854	200.84
6	Product mix=equal	119.8579	396.3288	142.5483	435.6142	60.23125	417.885	48.68542	247.47
7	Product mix=different	109.1342	309.605	198.0358	351.0475	64.81083	296.5738	49.60917	184.7167
8	Machine capacity=equal	108.8908	374.0229	154.5221	448.2196	60.80708	400.2542	47.91042	214.8825
9	Machine capacity=different	120.1013	331.9108	186.0621	338.4421	64.235	314.2046	50.38417	217.3042
10	Processing Time=equal	116.9533	356.0079	170.3492	383.1692	65.17958	375.4046	47.93083	224.0629
11	Processing Time=different	112.0388	349.9258	170.235	403.4925	59.8625	339.0542	50.36375	208.1238
12	Overall average	115.48	354.08	170.33	394.49	62.68	358.17	49.16	214.15

Table 4.3. Summary of the simulation results for bi-criteria problem: NACH-SUE is compared to the benchmark control strategies

		Cycle Time			Tardiness			Average		
No.	Average at:	Δ 1	Δ 2	Δ 3	Δ 1	Δ 2	Δ 3	Δ 1	Δ 2	Δ 3
1	Number of products=2	21.97	64.56	14.38	23.66	32.05	23.95	22.81	48.30	19.16
2	Number of products=5	67.78	74.62	25.87	47.55	52.71	48.42	57.66	63.66	37.15
3	Traffic intensity=0.2	1.58	84.11	1.57	28.83	45.52	31.72	15.20	64.82	16.64
4	Traffic intensity=0.5	34.72	57.85	14.64	48.19	50.35	51.50	41.46	54.10	33.07
5	Traffic intensity=0.8	78.64	54.18	39.65	43.81	45.95	38.61	61.22	50.06	39.13
6	Product mix=equal	59.38	65.85	19.17	37.56	43.19	40.78	48.47	54.52	29.97
7	Product mix=different	54.54	74.95	23.46	40.34	47.38	37.72	47.44	61.17	30.59
8	Machine capacity=equal	56.00	68.99	21.21	42.55	52.06	46.31	49.27	60.53	33.76
9	Machine capacity=different	58.05	72.92	21.56	34.53	35.79	30.84	46.29	54.36	26.20
10	Processing Time=equal	59.02	71.86	26.46	37.06	41.52	40.31	48.04	56.69	33.39
11	Processing Time=different	55.05	70.42	15.87	40.52	48.42	38.62	47.79	59.42	27.24
12	Overall average	57.43	71.14	21.58	39.52	45.71	40.21	48.48	58.43	30.89

Δ1 = 100* (No idle – NACH-SUE)/No idle

Δ2 = 100* (Full batch – NACH-SUE)/Full batch

Δ3 = 100* (MBS-SUE – NACH-SUE)/MBS-SUE

Table 4.4. Summary of the simulation results for bi-criteria problem: Approaches with the dynamic weight is compared to approaches with the static weight

		No idle			Full batch			MBS-SUE			NACH-SUE		
No.	Average at:	Static	Dynamic	Δ	Static	Dynamic	Δ	Static	Dynamic	Δ	Static	Dynamic	Δ
1	Number of products=2	246.706	156.32	36.64	324.2006	204.46	36.93	241.9067	154.45	36.15	159.3092	119.79	24.80
2	Number of products=5	440.4242	311.14	29.35	494.4735	359.16	27.36	332.6306	265.30	20.24	199.6173	145.45	27.14
3	Traffic intensity=0.2	303.3719	167.35	44.84	478.8703	326.53	31.81	301.1613	173.49	42.39	202.1347	125.12	38.10
4	Traffic intensity=0.5	330.2213	254.67	22.88	405.8275	287.49	29.16	286.9913	258.99	9.76	170.4897	137.75	19.21
5	Traffic intensity=0.8	391.725	290.71	25.79	324.7323	238.00	26.71	260.1197	203.22	21.88	151.5383	124.35	17.94
6	Product mix=equal	376.0706	258.09	31.37	436.0627	289.08	33.71	314.2013	239.06	23.92	198.5294	148.08	25.41
7	Product mix=different	311.0596	209.37	32.69	382.6115	274.54	28.25	260.336	180.69	30.59	160.3971	117.16	26.95
8	Machine capacity=equal	352.8277	241.46	31.57	395.3823	301.37	23.78	301.216	230.53	23.47	182.5348	131.40	28.02
9	Machine capacity=different	334.3025	226.01	32.39	423.2919	262.25	38.04	273.3213	189.22	30.77	176.3917	133.84	24.12
10	Processing Time=equal	353.8271	236.48	33.16	403.4033	276.76	31.39	292.1367	220.29	24.59	181.2004	136.00	24.95
11	Processing Time=different	333.3031	230.98	30.70	415.2708	286.86	30.92	282.4006	199.46	29.37	163.6869	129.24	21.04
12	Overall average	343.08	234.78	31.57	407.65	282.41	30.72	286.04	210.43	26.65	176.89	131.65	25.24

Δ = 100*(Static-Dynamic)/Static

The overall performance improvements gained by dynamic SUE function are 31.57%, 30.72%, 26.65%, 25.24% for No idle, full batch, MBS-SUE, NACH-SUE respectively. The performance improvements gained by No idle and full batch is more than NACH-SUE and MBS-SUE. This is due to the fact that NACH-SUE and MBS-SUE is superior to No idle and full batch therefore performance improvement using dynamic SUE function is less prominent than No idle and full batch.

Figure 4.2 indicates the trend in the percentage improvements gained by NACH-SUE for different number of products. Although improvement percentages for cycle time and tardiness do not have robust trend, the actual improvement values is significantly large. When number of products of 5 is compared to number of products of 2, better performance improvement is observed for number of product of 5. This result can be attributed to the fact that when there are more number of products, inter-arrival times for product type become longer since the ratio of each product in product mix decreases. In this case, NACH-SUE can consider more alternatives (process or wait) at each decision epoch and there are more decision epochs for more product types.

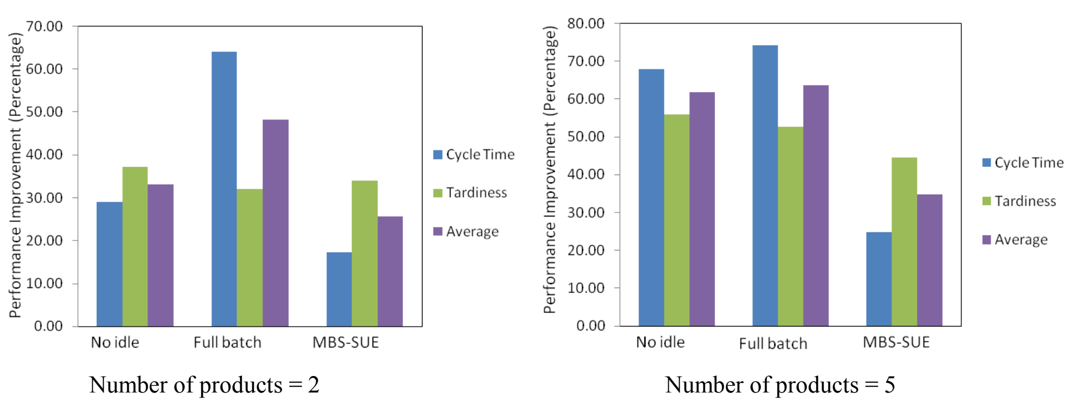
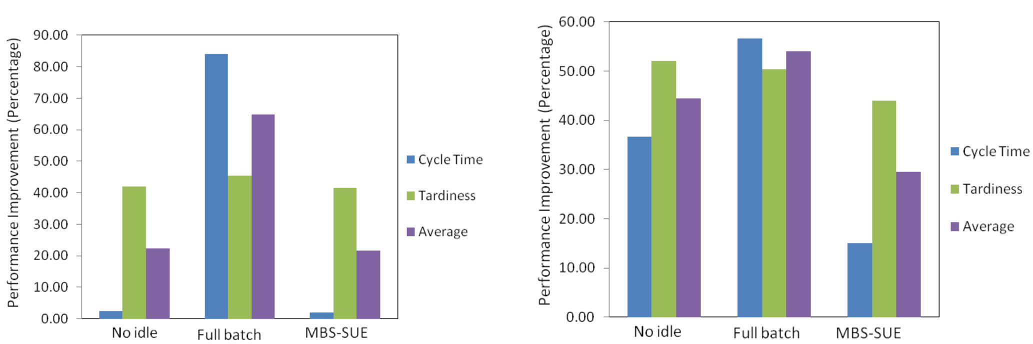


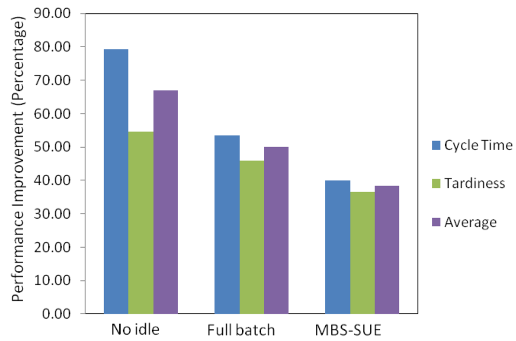
Fig. 4.2. Performance improvements observed for NACH-SUE for bi-criteria problem with different number of products

The performance improvement gained by NACH-SUE has a negative effect with increase in traffic intensity. Figure 4.3 shows that the performance improvement with increasing traffic intensity has a steady trend. At higher traffic intensity, the number of products waiting in queue at decision epoch becomes larger so full batch strategy is used as the decision often. This leads to more process with each strategy since all strategies use full batch strategy automatically when there are full batches in queue for multiple product types. Also, at low traffic intensity, performance improvement over no idle and MBS-SUE is similar since the best MBS at low traffic intensity is mostly low value of MBS which is similar to no idle strategy. On the other hand, at high traffic intensity, performance improvement over full batch is comparable to MBS-SUE since the best MBS at high traffic intensity is mostly high value of MBS which is similar to full batch strategy.



Traffic intensity = 0.2 Traffic intensity = 0.5

Fig. 4.3. Performance improvements observed for NACH-SUE for bi-criteria problem with traffic intensity



Traffic intensity = 0.8

Fig. 4.3. continued

There are no significant trends and changes in performance improvement at different product mix (see Figure 4.4). However there is a slight performance improvement for different product mix. A similar explanation discussed in the number of products is applicable in product mix case. When there is a dominant product type in product mix, the strategy works like the case of fewer product types. This phenomenon results in the improved performance.

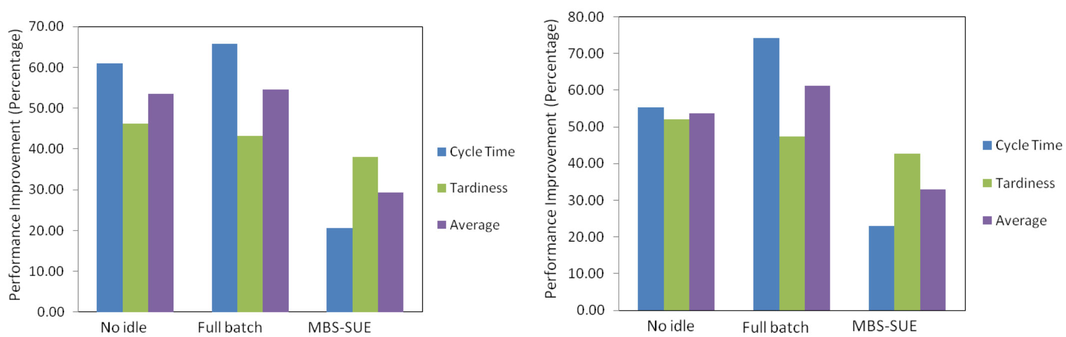
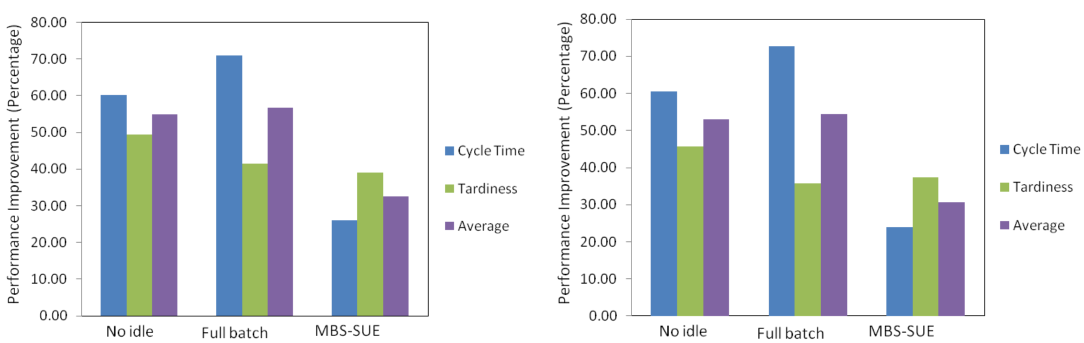


Fig. 4.4. Performance improvements observed for NACH-SUE for bi-criteria problem with product mix

There is no observed significant performance improvement trend for NACH-SUE with equal and different machine capacity (see Figure 4.5). This is due to SUE function effect. Even though a steady trend is expected when the machine capacity is unbalanced between product types, since the product mix is dominated by a few product types, utility value changing over time affects to stabilize the performance improvement. A dynamic weight is assigned to each product at every decision epoch to optimize based on multi-objective criteria. In this step, all attempts by different weights over time on each product affect both equal machine capacity and different machine capacity. This effect soothes the performance improvement gap between equal and different product mix.

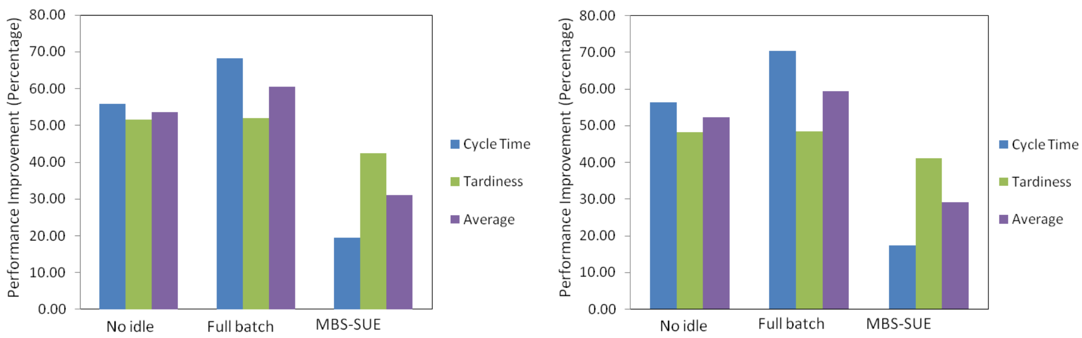


Machine capacity = Equal Machine capacity = Different

Fig. 4.5. Performance improvements observed for NACH-SUE for bi-criteria problem with machine capacity

Similar analysis with product mix can be performed for equal and different processing time. The performance improvement obtained by NACH-SUE does not have significant trend and change with equal and different processing time (see Figure 4.6).

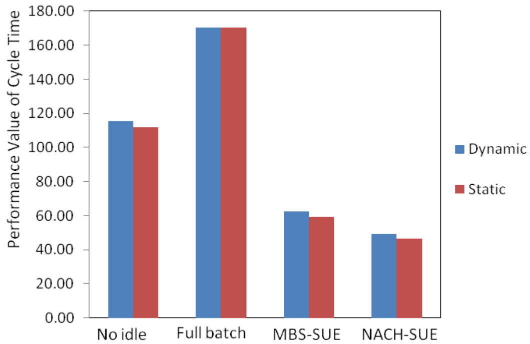
Even though processing time is unbalanced between product types, the SUE function plays a role in balancing the two attributes.



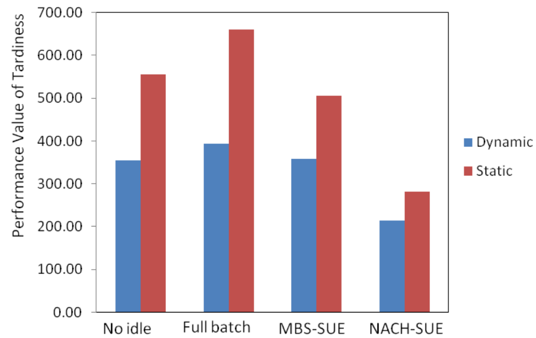
Processing time = Equal Processing time = Different

Fig. 4.6. Performance improvements observed for NACH-SUE for bi-criteria problem with processing time

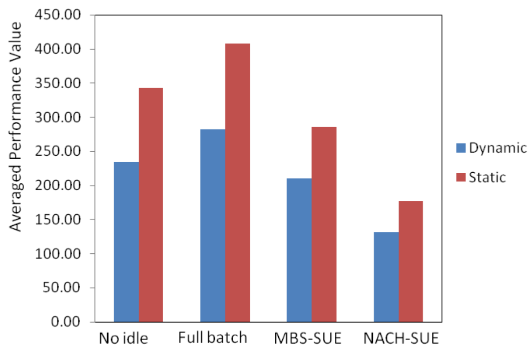
The performance (cycle time and tardiness) obtained by a dynamic strategy using SUE function is compared to the performance gained by a static strategy using fixed utility value over time (see Table 4.4). Figure 4.7 illustrates that cycle time decreases for all strategies. The interpretation of this result can be attributed to the fact that the existing strategies (NACH, MBS) use fixed utility values over time to minimize the cycle time only. On the other hand, even though cycle time is increasing when SUE function is used in the existing strategies, the strategies using SUE function optimize a multi-objective problem with cycle time and tardiness. In an overview of cycle time and tardiness, the performance using dynamic strategies is observed to be better than the performance using static strategies.



Performance of cycle time



Performance of tardiness



Averaged performance

Fig. 4.7. Comparison of performances observed for dynamic strategy and static strategy for bi-criteria problem with cycle time, tardiness and averaged over the two criteria

4.3 Contribution of the chapter

The contributions of the research provided in this chapter are the follow:

i) Using SUE function, the benchmark strategies, NACH-SUE and MBS-SUE are introduced in order to minimize bi-criteria (cycle time and tardiness). This shows that the SUE function can be plugged into existing models and worked effectively for benchmark strategies.

ii) Overall performance of strategies using SUE function is improved than the existing model using static utility value. Using simulation, it is found that NACH-

SUE strategy has the best performance, and shows performance improvement with respect to MBS-SUE, No idle and full batch strategies.

iii) Performance improvements observed for NACH-SUE are about 21.58 – 71.14% for averaged cycle time and 39.52-54.58 for averaged tardiness, and performance differences between dynamic and static strategies are about 25.24 – 31.57%, respectively. However, there is a loss for the cycle time in dynamic strategy as compared to static model. It shows that even though cycle time slightly increases in dynamic strategy (Static strategy is focused on minimizing cycle time; on the other hand, Dynamic strategy considers two criteria, cycle time and tardiness), the average performance for cycle time and tardiness is significantly improved.

CHAPTER V

APPLICATION OF SUE FUNCTION TO THE TRI-CRITERIA BATCH PROCESS CONTROL PROBLEM

In practical applications, a decision-maker has to consider multiple criteria. Due to complexity of problems and the trade-offs among criteria, few researchers have considered more than two criteria. Mathirajan and Sivakumar (2006a) have reviewed and categorized the research on batch process control problems into one criterion (cycle time, tardiness, average number of jobs, etc.) and bi-criteria (cycle time and tardiness, and earliness and tardiness). There is limited research on tri-criteria including cycle time, earliness and tardiness. This chapter shows how to apply the SUE function to the existing models for tri-criteria objective problems.

5.1 Modification of the benchmark strategy for tri-criteria problem

Using the SUE function for earliness and tardiness, a similar procedure can be applied to the triple objective approach as follows:

5.1.1 MBS-SUE for tri-criteria problem

Using the SUE function for earliness and tardiness, the weighted value remains constant (=1) when a job is expected on time, implying that there will be no earliness and tardiness (i.e. the SUE function has the value of “1”), since the weights for commodities are not changing. In this case, MBS-SUE behaves the same as the MBS model. Once a job is expected late or early (i.e. the weight for tardiness and earliness has the appropriate values from the SUE function), the results of the MBS-SUE approach will vary with the stochastic information of arrival such as types of arrival distribution and rate, traffic density, etc. For the multiple products case, the MBS-SUE for triple criteria is similar to the MBSX approach. When more than one type of products have greater than MBS value in the queue, the one with the longest weighted waiting time using the SUE function for earliness and tardiness is selected. When there is more than one nominee, the one with the shortest weighted processing time using the SUE function for earliness and tardiness is selected.

5.1.2 NACH-SUE approach for tri-criteria problem

Using the weight from the SUE function for earliness and tardiness, the gain and loss based on weighted value in the NACH rule is obtained, and the best epoch is decided to obtain the positive gain.

For the NACH-SUE for tri-criteria problem, the SUE function for earliness and tardiness is applied to the NACH approach. Therefore the additional loss for NACH-SUE caused by waiting for the future arrival at t_1 is calculated by

$$WArea_1(t) = W_{ET}(t) \times q(t_1 - t_0)$$

This area, which reflects the weighting value from the SUE function for earliness and tardiness, represents the total additional loss for the q lots that are in queue at t_0. The gain caused by waiting for the future arrival at t_1 is calculated by:

$WArea_2(t) = W_{ET}(t) \times (t_0 + T_j - t_1)$

Therefore, the net gain is given by

$WNet(t) = WArea_2(t) - WArea_1(t)$

Similar to the procedure for a single product case, NACH-SUE for multiple product types for earliness and tardiness follows NACH-SUE for tardiness as follows and is illustrated in Figure 5.1.

If the machine is idle,

If full batches are available,

Then choose a product

$j^* = arg\, min_{q_i \geq C_j} W_j \; (W_j = T_j \sum_{i \neq j} W_{ET_i}(t) \times q_i)$

and batch is processed.

Here, W_j is the total delay for the other products when the product *j* is processed.

The product j^* has minimum waiting time metric value among product types.

Else, evaluate $NACH_j$ for all *j*,

$$(NACH_j = \sum_{i=1, i \neq j}^{N} [W_{ET_i}(t) \times (q_i(t_{1,i} - t_0) - (t_0 + T_j - t_{1,i}))] \;)$$

If $j \in SY$,

then wait *($NACH_j < 0$, for all j = 1,…, N).*

Else,

If $j \in SN$ *($NACH_j \geq 0$, for all j = 1,…, N)*,

Here, *SY* is the set of j which needs to wait for a next arrival.

On the other hand, *SN* is the set of j which does not need to wait for a next arrival.

then choose $j^* = arg\, min_{j\in J}\, W_j$

Else,

$DNACH_j = W_j + \sum_{i=1}^{N} max\ (0, W_{ET_i}(t) \times (t_0 + T_j - t_{1,i}))\quad j \in SN$

$DNACH_j = \sum_{i=1}^{N}(W_{ET_i}(t) \times q_i(t_{1,i} - t_0)) + W_j + \sum_{i=1}^{N} max\ (0, W_{ET_i}(t) \times (t_0 + T_j - t_{1,i}))$
$j \in SY$

$DNACH_j$ is the total delay when product *j* loaded.

Choose a product $j^* = arg\, min_{j\in J}\ DNACH_j$

If $j^* \in SN,$ then batch is processed.

Else, wait.

If the machine is idle and a product j arrives,

Then proceed as indicated by $NACH_j$.

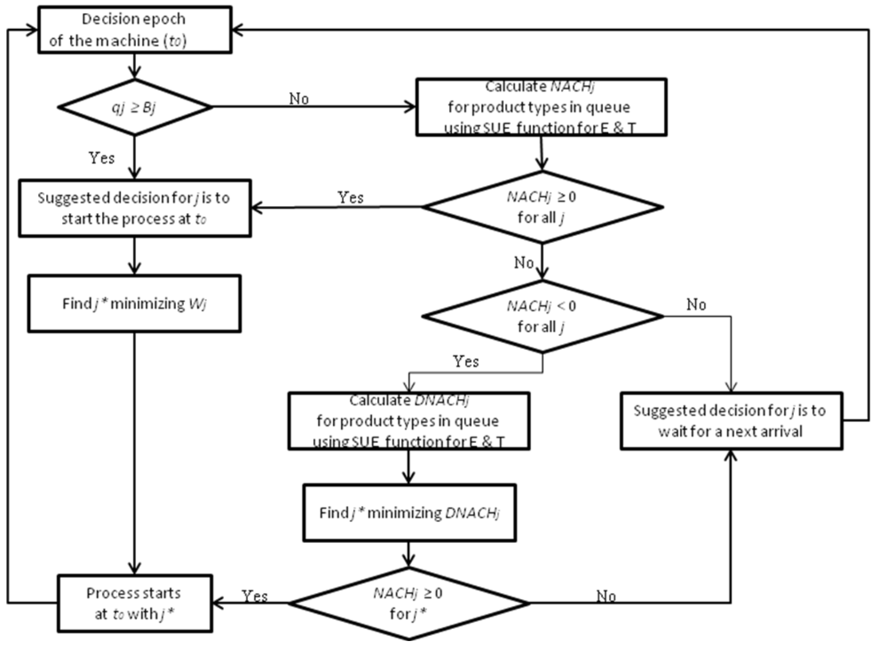


Fig. 5.1. Flow chart of the NACH-SUE algorithm for tri-criteria problem

5.1.3 Full batch approach for tri-criteria problem

This strategy is almost similar to full batch policy for bi-criteria problem. The difference is that a SUE function for earliness and tardiness is utilized in tri-criteria problem.

At the decision point t_0, if only one available full batch remains in queue, the batch proceeds with the full batch. When there is more than one type of products with full batch in the queue, the type with the longest weighted waiting time using SUE function for earliness and tardiness is selected. When there is more than one nominee, the one with the shortest weighted processing time using the SUE function for earliness and tardiness is selected.

5.1.4 No idle approach for tri-criteria problem

Similar to the full batch strategy, this strategy is also comparable to No idle policy for bi-criteria problem. Instead of the SUE function for tardiness, the SUE function for earliness and tardiness is utilized in tri-criteria problem.

At the decision epoch t_0, if more than one available full batch is available, the no-idling policy is the same as the full batch policy. On the other hand, if there are only partial batches, the one with the longest weighted waiting time using the SUE function for earliness and tardiness is selected. As with the full batch policy, when there is more than one nominee, the one with the shortest weighted processing time is selected.

5.2 Simulation results for tri-criteria problem

The performance of modification of the benchmark strategy is experimented under the same conditions for bi-criteria problem (see Table 5.1). Each of the control strategies is tested for each scenario.

A combination of the settings for simulation are:

i) Control strategy: NACH-SUE, MBS-SUE, Full batch, No idle

ii) Simulation run length: 100,000 time units

iii) Number of replication: 10 times

iv) Warm-up period: 5,000 time units

Table 5.1. Configuration of the simulation for tri-criteria problem

No.	Factors	Settings		
1	Number of Products (NP)	2		
	Number of Products (NP)	5		
2	Product Mix (PM)	Equal(E)	2 products	(0.5,0.5)
	Product Mix (PM)	Equal(E)	5 products	(0.2,0.2,0.2,0.2,0.2)
	Product Mix (PM)	Different(D)	2 products	(0.2,0.8)
	Product Mix (PM)	Different(D)	5 products	(0.1,0.1,0.1,0.35,0.35)
3	Machine Capacity by Product (MC)	Equal(E)	2 products	(5,5)
	Machine Capacity by Product (MC)	Equal(E)	5 products	(5,5,5,5,5)
	Machine Capacity by Product (MC)	Different(D)	2 products	(3,7)
	Machine Capacity by Product (MC)	Different(D)	5 products	(3,4,5,6,7)
4	Processing Time by Product (PT)	Equal(E)	2 products	(25,25)
	Processing Time by Product (PT)	Equal(E)	5 products	(25,25,25,25,25)
	Processing Time by Product (PT)	Different(D)	2 products	(10,40)
	Processing Time by Product (PT)	Different(D)	5 products	(10,20,25,30,40)
5	Traffic Intensity (TI)	0.2		
	Traffic Intensity (TI)	0.5		
	Traffic Intensity (TI)	0.8		

The equation for traffic intensity is

$$\lambda_j = \rho / \sum_{j=1}^{N} \frac{P_j T_j}{B_j}$$

where

$$\lambda_j = \text{Mean arrival rate for product } j$$

$$\rho = \text{Batch processor traffic intensity}$$

$$P_j = \text{Product mix}$$

$$T_j = \text{Batch process time}$$

$$B_j = \text{Batch processor capacity for product } j$$

The value of number of order and due date have been chosen for each scenario as follow:

$$N_j = S/\rho \times \sum_{j=1}^{N} \frac{P_j B_j}{T_j}$$

where

S = Standard number of order when all factors (PM, MC, PT) have equal values

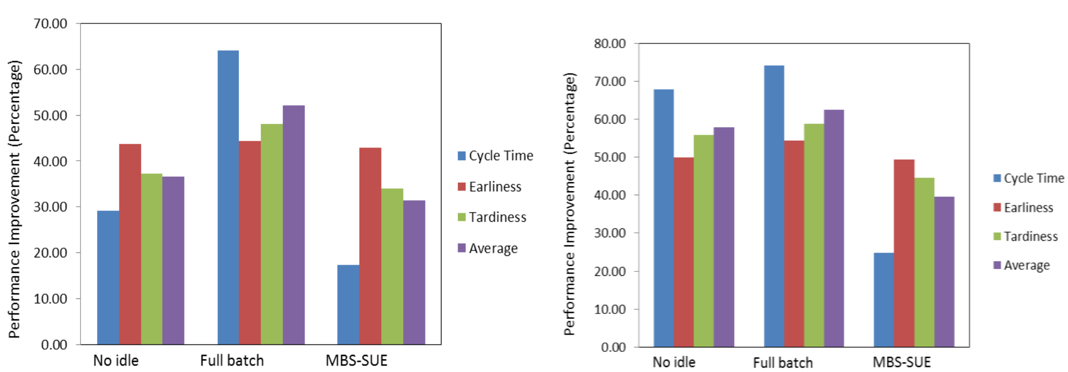
$$D_j = \lambda_j \times N_j$$

The experiment of control strategies provide 48 (2x24) scenarios. Each scenario is simulated with each of the control strategies. Every scenario is set up with a run-time of 100,000 time units, a warm up time of 5,000 time units and 10 replications. Pentium dual core 3.20 GHz processor and 2 GB RAM is used for the scenario and Matlab 7.5 is used for the simulation code.

This chapter describes the performance (cycle time, earliness and tardiness) of NACH-SUE, MBS-SUE, No idle and full batch, and the performance is compared to each other. Tables 5.2, 5.3 and 5.4 summarize the simulation results. The results in the tables are averaged over different settings of the product, machine and process characteristics.

Experimental results in tables 5.2 and 5.3 show that the best performance rule is NACH-SUE. The closest performing approach to NACH-SUE is MBS-SUE since MBS-SUE strategy chooses the best MBS to maximize the performance. On the other hand, no idle rule and full batch rule has a lower performance since no idle rule does not allow waiting for next arrival and full batch rule is waiting for next arrival by full batch in queue. Table 5.4 presents the trend of performance improvements when SUE function for earliness and tardiness is used in the strategies. Dynamic control strategy where utility value for earliness and tardiness is changing over time has significant performance improvement than static control strategy (where utility value is fixed over time).

Figure 5.2 indicates performance improvement gained by NACH-SUE with increasing number of products. Although improvement percentages for cycle time, earliness and tardiness do not have a robust trend, the actual improvement values are significantly large. There is a significant performance improvement with a larger number of products (number of products of 5 compared to number of products of 2). This is due to the fact that NACH-SUE can consider more alternatives (process or wait) at each decision epoch and there are more decision epochs for number of products = 5.



Number of products = 2　　　　Number of products = 5

Fig. 5.2. Performance improvements observed for NACH-SUE for tri-criteria problem with number of products

Table 5.2. Summary of the simulation results for tri-criteria problem

No.	Average at:	No idle			Full batch			MBS-SUE			NACH-SUE		
		CT	earliness	tardiness	CT	earliness	tardiness	CT	earliness	tardiness	CT	earliness	tardiness
1	Number of products=2	59.07	561.20	358.61	116.54	567.92	433.68	50.67	553.31	341.28	41.89	316.29	225.13
2	Number of products=5	180.37	808.76	589.80	224.06	888.52	630.24	77.09	798.50	468.82	57.95	404.78	260.06
3	Traffic intensity=0.2	44.95	864.15	413.32	274.24	942.13	555.00	44.73	862.53	408.98	43.83	449.68	239.44
4	Traffic intensity=0.5	90.24	645.97	502.94	132.09	678.93	576.84	67.35	640.96	429.71	57.20	328.57	240.82
5	Traffic intensity=0.8	235.50	467.88	487.48	105.09	483.47	429.89	81.43	446.51	349.22	48.85	290.26	221.41
6	Product mix=equal	124.95	669.01	517.85	142.59	699.79	607.80	61.35	658.63	449.79	48.73	354.22	278.96
7	Product mix=different	114.49	700.96	430.56	198.01	756.65	456.11	66.41	693.18	360.31	51.11	366.85	206.23
8	Machine capacity=equal	111.66	531.89	504.63	155.56	575.96	527.33	61.25	526.41	424.93	49.31	321.19	244.24
9	Machine capacity=different	127.77	838.08	443.79	185.04	880.48	536.58	66.51	825.40	385.17	50.53	399.89	240.94
10	Processing Time=equal	123.64	475.15	491.60	169.82	513.91	507.67	66.54	468.09	408.14	49.20	280.67	248.47
11	Processing Time=different	115.79	894.81	456.82	170.77	942.53	556.24	61.23	883.72	401.96	50.64	440.40	236.71
12	Overall average	120.77	677.99	472.49	170.35	720.94	528.85	64.05	668.84	402.57	49.93	359.34	240.22

Table 5.3. Summary of the simulation results for tri-criteria problem: NACH-SUE is compared to the benchmark control strategies

No.	Average at:	Cycle Time			Earliness			Tardiness			Average		
		Δ1	Δ 2	Δ 3	Δ 1	Δ 2	Δ 3	Δ 1	Δ 2	Δ 3	Δ 1	Δ 2	Δ 3
1	Number of products=2	29.10	64.06	17.34	43.64	44.31	42.84	37.22	48.09	34.03	36.65	52.15	31.40
2	Number of products=5	67.87	74.14	24.83	49.95	54.44	49.31	55.91	58.74	44.53	57.91	62.44	39.56
3	Traffic intensity=0.2	2.48	84.02	2.01	47.96	52.27	47.87	42.07	56.86	41.45	30.84	64.38	30.44
4	Traffic intensity=0.5	36.62	56.70	15.07	49.14	51.60	48.74	52.12	58.25	43.96	45.96	55.52	35.92
5	Traffic intensity=0.8	79.25	53.51	40.00	37.96	39.96	34.99	54.58	48.50	36.60	57.27	47.32	37.20
6	Product mix=equal	61.00	65.83	20.58	47.05	49.38	46.22	46.13	54.10	37.98	51.40	56.44	34.93
7	Product mix=different	55.36	74.19	23.04	47.66	51.52	47.08	52.10	54.79	42.76	51.71	60.16	37.63
8	Machine capacity=equal	55.84	68.30	19.50	39.61	44.23	38.99	51.60	53.68	42.52	49.02	55.41	33.67
9	Machine capacity=different	60.46	72.69	24.04	52.29	54.58	51.55	45.71	55.10	37.44	52.82	60.79	37.68
10	Processing Time=equal	60.21	71.03	26.06	40.93	45.39	40.04	49.46	51.06	39.12	50.20	55.82	35.07
11	Processing Time=different	56.27	70.35	17.30	50.78	53.27	50.17	48.18	57.44	41.11	51.74	60.36	36.19
12	Overall average	58.66	70.69	22.05	47.00	50.16	46.27	49.16	54.58	40.33	51.60	58.47	36.22

Δ1 = 100* (No idle – NACH-SUE)/No idle

Δ2 = 100* (Full batch – NACH-SUE)/Full batch

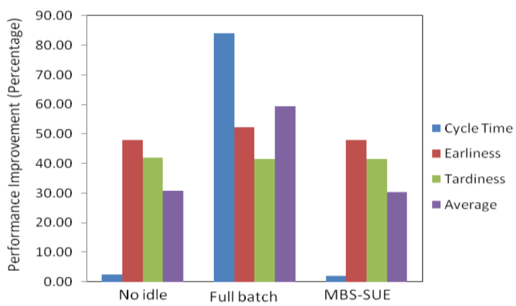
Δ3 = 100* (MBS-SUE – NACH-SUE)/MBS-SUE

Table 5.4. Summary of the simulation results for tri-criteria problem: Approaches with the dynamic weight is compared to approaches with the static weight

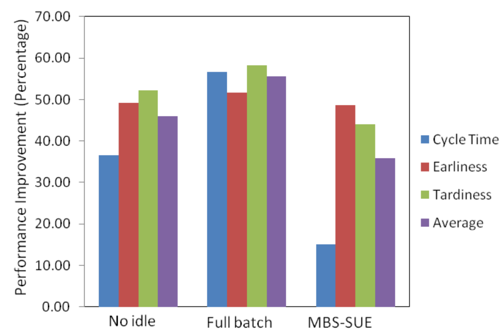
No.	Average at:	No idle			Full batch			MBS-SUE			NACH-SUE		
		Static	Dynamic	Δ	Static	Dynamic	Δ	Static	Dynamic	Δ	Static	Dynamic	Δ
1	Number of products=2	338.03	232.76	31.14	319.71	278.06	13.03	242.76	222.87	8.19	171.38	141.72	17.31
2	Number of products=5	443.31	391.52	11.68	488.48	432.85	11.39	369.26	315.05	14.68	205.76	173.47	15.69
3	Traffic intensity=0.2	484.49	296.78	38.74	487.12	433.43	11.02	346.17	294.99	14.78	224.67	169.37	24.61
4	Traffic intensity=0.5	320.20	305.39	4.63	394.32	349.46	11.37	291.37	272.51	6.47	175.07	154.10	11.98
5	Traffic intensity=0.8	349.50	318.97	8.73	304.83	258.91	15.06	257.23	217.97	15.26	153.74	138.46	9.93
6	Product mix=equal	467.94	325.77	30.38	415.87	366.76	11.81	333.64	280.15	16.03	203.34	168.27	17.25
7	Product mix=different	313.40	298.51	4.75	392.32	344.15	12.28	278.38	257.77	7.40	173.80	146.92	15.47
8	Machine capacity=equal	419.91	294.08	29.97	367.48	323.63	11.93	293.13	249.80	14.78	183.90	151.38	17.68
9	Machine capacity=different	361.44	330.20	8.64	440.71	387.29	12.12	318.88	288.13	9.64	193.24	163.80	15.23
10	Processing Time=equal	328.70	284.27	13.52	365.24	311.48	14.72	285.70	236.24	17.31	177.57	146.00	17.78
11	Processing Time=different	452.64	340.01	24.88	442.94	399.43	9.82	326.31	301.68	7.55	199.57	169.18	15.23
12	Overall average	389.05	310.75	20.13	401.73	353.22	12.07	303.89	267.02	12.14	187.46	156.61	16.46

Δ = 100*(Static-Dynamic)/Static

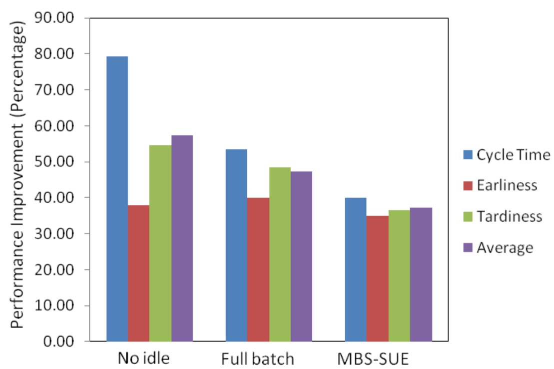
Figure 5.3 shows that there is a steady performance improvement with increasing traffic intensity. This is due to the fact that with higher traffic intensities, the number of products in queue becomes larger and full batch is observed often. This leads to just start the process without idling and operate the machine with full machine capacity. At low traffic intensity, performance improvement over no idle and MBS-SUE is similar to each other since the best MBS at low traffic intensity is mostly low value of MBS which is similar to no idle strategy. On the other hand, at high traffic intensity, performance improvement over full batch is comparable to MBS-SUE since the best MBS at high traffic intensity is mostly high value of MBS which is similar to full batch strategy.



Traffic intensity = 0.2



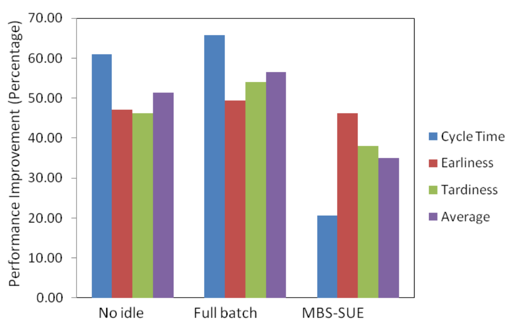
Traffic intensity = 0.5



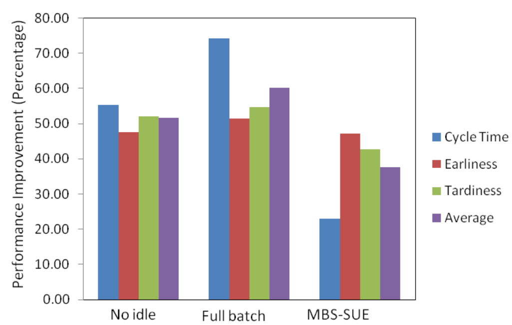
Traffic intensity = 0.8

Fig. 5.3. Performance improvements observed for NACH-SUE for tri-criteria problem with traffic intensity

There are no significant trend and change in performance improvement at different machine capacities (see Figure 5.4). The results show that performance is better when the machine capacity is equal, this is due to the fact that equal capacity leads to a balanced batching and processing. Improvements over MBS-SUE are less than others. It is due to the fact that MBS strategy chooses the best MBS among available MBSs. Available MBSs include MBS of 1 which is equal to no idle strategy, and MBS of machine capacity which is equal to full batch strategy.



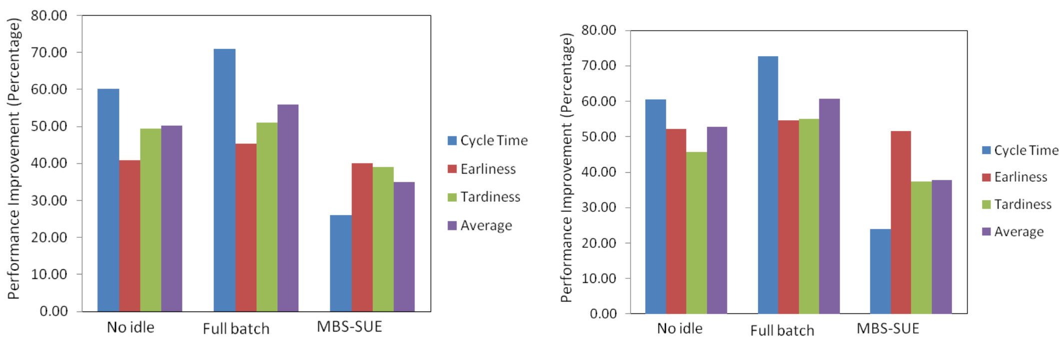
Machine capacity = Equal



Machine capacity = Different

Fig. 5.4. Performance improvements observed for NACH-SUE for tri-criteria problem with machine capacity

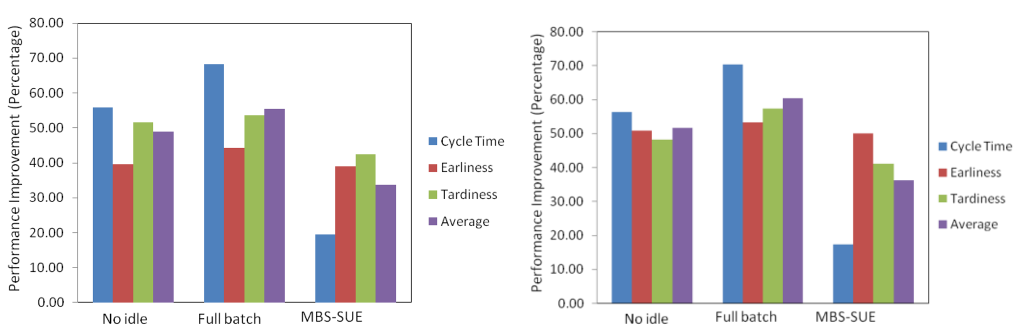
The performance improvement obtained by NACH-SUE does not present any significant trend and change with equal and different product mix (see Figure 5.5). This is due to SUE function effect. Even though a steady trend is expected when the product mix is unbalanced as the product mix is dominated by a few product types, SUE function affects to stabilize the performance improvement for all criteria (cycle time, earliness and tardiness). The dynamic weight is given to each product at decision epoch to optimize based on multi-objective criteria. In this step, all attempts by different weights over time on each product affect both equal product mix and different mix. This effect soothes the performance improvement gap between equal and different product mix.



Product mix = Equal Product mix = Different

Fig. 5.5. Performance improvements observed for NACH-SUE for tri-criteria problem with product mix

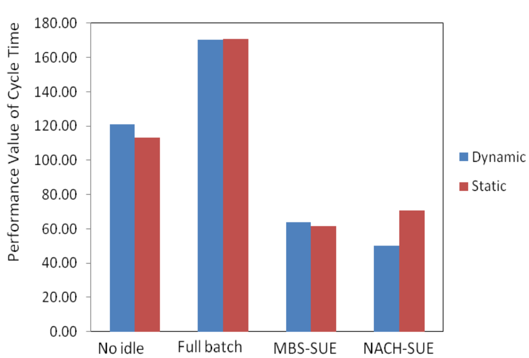
Similar analysis with product mix can be performed for equal and different processing time. The performance improvement obtained by NACH-SUE does not show any significant trend and change with equal and different processing time (see Figure 5.6). Even though processing time is unbalanced between product types, the SUE function plays a role in balancing the two attributes.



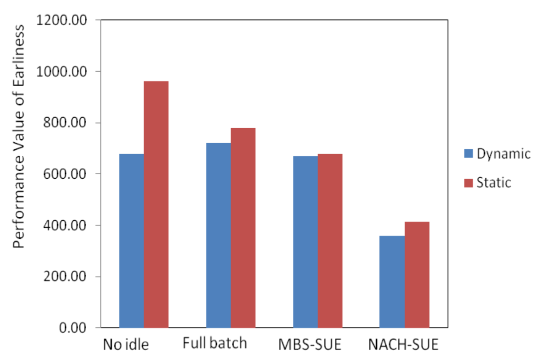
Processing time = Equal Processing time = Different

Fig. 5.6. Performance improvements observed for NACH-SUE for tri-criteria problem with processing time

The performance (cycle time, earliness and tardiness) obtained by dynamic strategy using SUE function is compared to the performance gained by static strategy using fixed utility value over time (see Table 5.4). Figure 5.7 illustrates that cycle time decreases or almost remains the same for all strategies. The interpretation of this result is due to the fact that the existing strategies (NACH, MBS, etc.) use fixed utility values over time to minimize the cycle time only. On the other hand, even though cycle time is increasing when SUE function is used in the existing strategies, the strategies using SUE function attempt to optimize a multi-objective problem with attributes cycle time, earliness and tardiness. In an overview of earliness and tardiness, the results obtained from dynamic strategies are better than the results from static strategies. As a result, there is an improvement in total averaged performance including cycle time, earliness and tardiness using a dynamic strategy as compared to a static strategy.

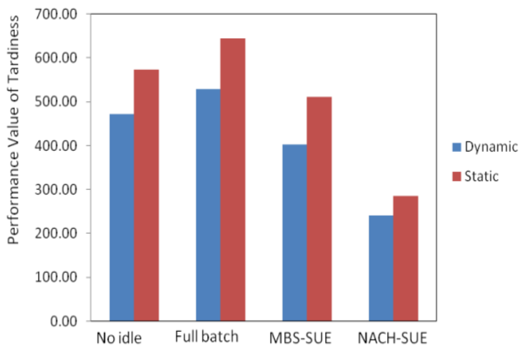


Performance of cycle time

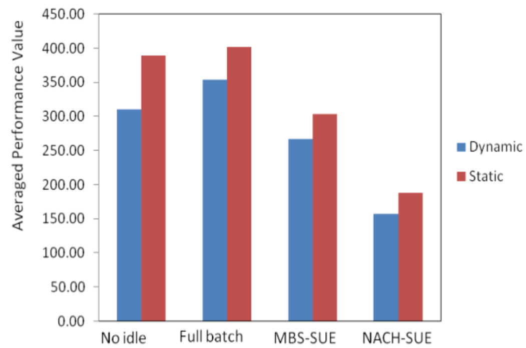


Performance of earliness

Fig. 5.7. Comparison of performances observed for dynamic strategy and static strategy for tri-criteria problem with cycle time, earliness, tardiness and averaged all criteria



Performance of tardiness



Averaged performance

Fig. 5.7. continued

5.3 Contribution of the chapter

The contributions of the research provided in this chapter are the follow:

i) The main contribution of this chapter is to solve tri-criteria problem which has not been studied extensively. This chapter provides SUE function for earliness and tardiness, and then this function is applied to the benchmark strategy such as NACH-SUE and MBS-SUE in order to minimize tri-criteria (cycle time and earliness/tardiness). This shows that the SUE function can consider more than two criteria simultaneously and with the use of this function, multi-objective problem can be solved with the combined strategy.

ii) Similar to strategies for solving bi-criteria problem, the performance of strategies for cycle time, earliness and tardiness using SUE function is improved than the existing model using static utility value. More importantly, it is found that the NACH-SUE strategy has the most performance improvement with respect to MBS-SUE, No idle and full batch strategies.

iii) Performance improvement of NACH-SUE over the other benchmark strategies does not have significant changes with respect to number of products, machine capacity and processing time except traffic intensities among all scenarios. Performance improvements observed for NACH-SUE are in the range of 28.5 – 45.4%, and performance differences between dynamic and static strategies are in the range of 12.1 – 20.1%, respectively. However, among all criteria, the cycle time has been increased in dynamic strategy than static model. It shows that even though the performance for cycle time is increased in dynamic strategy, an overall performance for tri-criteria is significantly improved in dynamic strategy.

CHAPTER VI

CONCLUSIONS, CONTRIBUTIONS AND FUTURE RESEARCH DIRECTIONS

6.1 Conclusions and contributions of the dissertation

This dissertation shows that there is potential benefit in using SUE function in the benchmark strategies. The SUE function has been developed to reflect the changing weight of each product type over time affected by the due date and storage cost. This function can be plugged into the existing strategies to solve multi-criteria problem. These proposed strategies which that have been developed by combining the SUE function with the existing approach have been experimentally shown to improve mean performance over all criteria (cycle time and tardiness or cycle time, earliness and tardiness).

In Chapter III, a SUE function that provides the weight of each product type at decision epoch was proposed and a variety of SUE functions considering tardiness only, earliness only and both earliness and tardiness have been developed. The existing approaches use fixed weight for a criterion over time. This chapter has explained why the SUE function is useful for existing approaches and how to derive this. The proposed SUE function introduces objectivity since SUE function is not derived from a decision maker's subjective intuition but stochastic information which is more objective than a decision maker's opinion.

In Chapter IV, using the SUE function, the modified benchmark strategies NACH-SUE and MBS-SUE are developed to improve the performance of the system for a bi-criteria (cycle time and tardiness) problem. A simulation-based study was performed to compare the performance of the developed benchmark strategies. Overall performance improvement of the strategies using SUE function is observed over the existing strategies which use a static utility value. Especially, the NACH-SUE strategy has the most observed performance improvement. The simulation results have been analysed and compared with the performance of each strategy, the trend and change to show the performance difference. Performance improvement of NACH-SUE with respect to MBS-SUE, No idle and full batch does not have significant trend with most simulation scenarios. The SUE function appears to have a soothing effect on the overall performance of the system when there is an imbalance of product mix, number of products and processing times. Performance improvements have been observed for NACH-SUE over No idle, full batch and MBS-SUE, and for dynamic strategy over static strategy.

Chapter V demonstrated how the SUE function operates in the existing model to solve tri-criteria problem. Similar to bi-criteria problem, the proposed approach for tri-criteria problem, namely NACH-SUE and MBS-SUE for tri-criteria problem have improved the averaged performance of each strategy for all criteria. Experimental results show that NACH-SUE has the most performance compared to the other benchmark strategies. This chapter also analyses the simulation results and compares the proposed strategies with the performance, trend and change. The analysis of the results is similar to the proposed approach for bi-criteria problem. Performance improvement of NACH-SUE over MBS-SUE, No idle and full batch does not have significant trend and change with most scenarios when there is an imbalance of product mix, number of products and processing times. Performance improvements have been observed significantly for NACH-SUE over No idle, full batch and MBS-SUE, and also for dynamic strategy over static strategy.

Finally, based on the analysis in Chapters III, IV and V, the supplementary contributions and potential applications to industry can be shown as listed below.

First, this research recognizes that the weight of products for earliness and tardiness changes over time and develops a method to incorporate this in existing methods with the help of a SUE function. Second, when a change in earliness and tardiness factors occur, only the SUE function is needed to account for the change. This makes the SUE function easy to use and does not affect the entire model. Finally, the SUE function can be applied easily to existing methods as demonstrated in this dissertation with MBS-SUE and NACH-SUE. The SUE function provides the mechanism to solve multi-criteria decision making problems. A bi and tri-criteria problem is used in this dissertation as an example to demonstrate its applicability.

6.2 Future research directions

This dissertation provides the potential benefit for the dynamic control for batch process systems. While this dissertation demonstrates several advantages of the proposed approaches, the issues for future research still remain and are planned along several lines.

First topic for future research is that the SUE function can be applied to other existing dynamic control of serial/batching processing systems. The advantage of the SUE function is easy to apply to the various existing models. At the decision epoch for most strategies, when the due date and storage cost are considered, the weight of each product type is necessary to reflect the cost for earliness and tardiness. SUE function can play a role to provide the weight of each product type at the decision epoch. Other existing models can be easily extended for multi-criteria problem with the use of SUE function. This makes it easier to use.

Second, the approach in this dissertation can be extended to multiple batch processor scenarios. This might need more considerations such as whether the SUE function for each product type for single batch processor also can be utilized in multiple batch processors or a new SUE function for each batch processor needs to be developed to solve the multiple batch processors problem.

Third, estimation of the SUE function needs to be explored further. Even though the methodologies using SUE function are more objective than the approach for multi-criteria depending on decision maker's opinion, this dissertation just has used the probability of stochastic process to derive the SUE function. However, the SUE function is still necessary to be improved to support the objectiveness.

Finally, due date information can be the future research topic. In this dissertation, due dates of each product type are assumed to be strict points over time. However, generally due dates are determined by the customer with the agreement of order and this means that there is an uncertainty in choosing due dates of each product type. Hence, the approach considering due dates in an uncertainty interval can be experimented in order to reflect more practical cases for due dates.

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APPENDIX A

PAIRED-T TEST FOR CHAPTER IV

The production characteristics and settings used in paired-t test are as follows:

No.	Factor	Setting		
1	Number of Products (NP)	2		
	Number of Products (NP)	5		
2	Product Mix (PM)	Equal(E)	2 products	(0.5,0.5)
	Product Mix (PM)	Equal(E)	5 products	(0.2,0.2,0.2,0.2,0.2)
	Product Mix (PM)	Different(D)	2 products	(0.2,0.8)
	Product Mix (PM)	Different(D)	5 products	(0.1,0.1,0.1,0.35,0.35)
3	Machine Capacity by Product (MC)	Equal(E)	2 products	(5,5)
	Machine Capacity by Product (MC)	Equal(E)	5 products	(5,5,5,5,5)
	Machine Capacity by Product (MC)	Different(D)	2 products	(3,7)
	Machine Capacity by Product (MC)	Different(D)	5 products	(3,4,5,6,7)
4	Processing Time by Product (PT)	Equal(E)	2 products	(25,25)
	Processing Time by Product (PT)	Equal(E)	5 products	(25,25,25,25,25)
	Processing Time by Product (PT)	Different(D)	2 products	(10,40)
	Processing Time by Product (PT)	Different(D)	5 products	(10,20,25,30,40)
5	Traffic Intensity (TI)	0.2		
	Traffic Intensity (TI)	0.5		
	Traffic Intensity (TI)	0.8		

Δ = The mean of the normalized differences for cycle time and tardiness obtained by 10 replications of NACH-SUE and the other strategies that the column belongs to. For example, if X~MBS-SUE and Y~NACH-SUE then,

$$\Delta = \frac{1}{10}\sum_{i=1}^{10}(X_i - Y_i)$$

σ = The standard deviation of the replication differences

conf = The half-width of the 95% confidence interval of the replication differences

sign = + if there is a significant performance difference observed with NACH-SUE

- if there is not a significant performance difference observed with NACH-SUE

a) Comparison of NACH-SUE with the other benchmarks

MBS-SUE

						Δ		σ		conf		sign	
No	NP	TI	PM	MC	PT	CT	Tar	CT	Tar	CT	Tar	CT	Tar
1	2	0.2	E	E	E	0.950	-2.075	2.004	0.114	0.040	0.002	+	-
2	2	0.2	E	E	D	1.634	481.615	1.364	23.891	0.027	0.474	+	+
3	2	0.2	E	D	E	-1.042	-411.725	2.038	7.604	0.040	0.151	-	-
4	2	0.2	E	D	D	0.706	-14.772	1.446	10.328	0.029	0.205	+	-
5	2	0.2	D	E	E	-0.496	-27.562	1.463	0.751	0.029	0.015	-	-
6	2	0.2	D	E	D	-8.700	252.528	1.415	15.341	0.028	0.304	-	+
7	2	0.2	D	D	E	0.733	18.044	2.031	3.537	0.040	0.070	+	+
8	2	0.2	D	D	D	-0.362	15.915	1.696	7.738	0.034	0.153	-	+
9	2	0.5	E	E	E	11.506	155.202	1.288	7.673	0.026	0.152	+	+
10	2	0.5	E	E	D	6.530	179.925	1.676	20.242	0.033	0.401	+	+
11	2	0.5	E	D	E	10.187	30.229	1.919	10.399	0.038	0.206	+	+
12	2	0.5	E	D	D	-3.163	7.324	2.076	5.384	0.041	0.107	-	+
13	2	0.5	D	E	E	11.031	118.180	1.923	4.353	0.038	0.086	+	+
14	2	0.5	D	E	D	-7.867	295.808	1.634	13.047	0.032	0.259	-	+
15	2	0.5	D	D	E	27.302	112.593	1.533	18.202	0.030	0.361	+	+
16	2	0.5	D	D	D	-5.201	82.651	1.574	7.443	0.031	0.148	-	+
17	2	0.8	E	E	E	13.402	86.537	1.641	5.772	0.033	0.114	+	+
18	2	0.8	E	E	D	15.845	121.811	1.442	14.896	0.029	0.295	+	+
19	2	0.8	E	D	E	13.658	57.312	2.503	10.860	0.050	0.215	+	+
20	2	0.8	E	D	D	-1.259	82.078	1.112	2.541	0.022	0.050	-	+
21	2	0.8	D	E	E	22.835	93.907	1.880	7.298	0.037	0.145	+	+
22	2	0.8	D	E	D	8.236	73.080	1.078	9.338	0.021	0.185	+	+
23	2	0.8	D	D	E	45.526	83.846	2.258	9.655	0.045	0.191	+	+
24	2	0.8	D	D	D	4.859	-379.323	1.961	12.600	0.039	0.250	+	-
25	5	0.2	E	E	E	4.987	-104.500	2.174	3.387	0.043	0.067	+	-
26	5	0.2	E	E	D	3.686	267.744	1.335	22.063	0.026	0.438	+	+
27	5	0.2	E	D	E	4.591	607.052	1.738	39.917	0.034	0.792	+	+
28	5	0.2	E	D	D	0.302	79.417	1.979	2.537	0.039	0.050	+	+
29	5	0.2	D	E	E	-1.379	103.144	1.846	3.666	0.037	0.073	-	+
30	5	0.2	D	E	D	0.290	121.922	1.024	16.691	0.020	0.331	+	+
31	5	0.2	D	D	E	0.913	135.840	1.862	7.713	0.037	0.153	+	+
32	5	0.2	D	D	D	2.509	24.571	1.627	1.069	0.032	0.021	+	+
33	5	0.5	E	E	E	4.904	567.882	2.728	17.613	0.054	0.349	+	+
34	5	0.5	E	E	D	6.030	506.344	4.562	33.854	0.090	0.671	+	+
35	5	0.5	E	D	E	18.604	414.537	2.671	21.074	0.053	0.418	+	+
36	5	0.5	E	D	D	8.691	157.086	3.732	5.014	0.074	0.099	+	+
37	5	0.5	D	E	E	21.020	199.237	2.958	14.010	0.059	0.278	+	+
38	5	0.5	D	E	D	6.230	131.949	2.975	12.806	0.059	0.254	+	+

39	5	0.5	D	D	E	39.864	659.714	3.952	29.357	0.078	0.582	+	+
40	5	0.5	D	D	D	-2.110	133.220	2.811	5.351	0.056	0.106	-	+
41	5	0.8	E	E	E	36.526	182.240	2.226	16.441	0.044	0.326	+	+
42	5	0.8	E	E	D	35.057	325.186	2.511	23.185	0.050	0.460	+	+
43	5	0.8	E	D	E	43.248	295.464	3.555	14.664	0.070	0.291	+	+
44	5	0.8	E	D	D	41.209	61.225	2.681	4.877	0.053	0.097	+	+
45	5	0.8	D	E	E	52.519	248.306	2.971	18.647	0.059	0.370	+	+
46	5	0.8	D	E	D	61.393	115.367	3.261	5.813	0.065	0.115	+	+
47	5	0.8	D	D	E	36.097	27.186	2.694	20.037	0.053	0.397	+	+
48	5	0.8	D	D	D	45.794	41.581	3.929	3.314	0.078	0.066	+	+

Full Batch

						Δ		σ		conf		sign	
No	**NP**	**TI**	**PM**	**MC**	**PT**	**CT**	**Tar**	**CT**	**Tar**	**CT**	**Tar**	**CT**	**Tar**
1	2	0.2	E	E	E	89.408	81.833	4.169	2.794	0.083	0.055	+	+
2	2	0.2	E	E	D	92.377	252.808	3.885	18.096	0.077	0.359	+	+
3	2	0.2	E	D	E	143.959	-426.234	5.203	7.924	0.103	0.157	+	-
4	2	0.2	E	D	D	115.908	173.634	5.809	16.530	0.115	0.328	+	+
5	2	0.2	D	E	E	143.011	27.350	4.657	1.752	0.092	0.035	+	+
6	2	0.2	D	E	D	138.963	366.573	6.405	10.687	0.127	0.212	+	+
7	2	0.2	D	D	E	212.201	39.362	5.070	5.565	0.101	0.110	+	+
8	2	0.2	D	D	D	209.953	19.338	3.895	4.950	0.077	0.098	+	+
9	2	0.5	E	E	E	34.952	118.400	2.462	8.229	0.049	0.163	+	+
10	2	0.5	E	E	D	30.827	208.093	1.536	23.736	0.030	0.471	+	+
11	2	0.5	E	D	E	48.971	28.707	2.523	4.052	0.050	0.080	+	+
12	2	0.5	E	D	D	30.562	164.802	3.357	7.745	0.067	0.154	+	+
13	2	0.5	D	E	E	51.270	151.324	2.636	5.728	0.052	0.114	+	+
14	2	0.5	D	E	D	68.937	310.829	4.787	14.835	0.095	0.294	+	+
15	2	0.5	D	D	E	81.778	239.454	2.512	13.643	0.050	0.271	+	+
16	2	0.5	D	D	D	72.223	79.516	4.498	6.197	0.089	0.123	+	+
17	2	0.8	E	E	E	19.820	94.672	2.361	8.403	0.047	0.167	+	+
18	2	0.8	E	E	D	22.623	135.288	2.054	8.739	0.041	0.173	+	+
19	2	0.8	E	D	E	31.332	57.977	2.574	8.262	0.051	0.164	+	+
20	2	0.8	E	D	D	15.476	131.655	1.968	4.686	0.039	0.093	+	+
21	2	0.8	D	E	E	35.600	131.118	2.221	8.459	0.044	0.168	+	+
22	2	0.8	D	E	D	33.367	157.421	2.591	6.006	0.051	0.119	+	+
23	2	0.8	D	D	E	57.997	44.115	2.869	8.105	0.057	0.161	+	+
24	2	0.8	D	D	D	51.574	-367.946	3.889	13.608	0.077	0.270	+	-
25	5	0.2	E	E	E	242.640	-25.330	9.274	3.334	0.184	0.066	+	-
26	5	0.2	E	E	D	239.672	769.318	8.583	28.438	0.170	0.564	+	+
27	5	0.2	E	D	E	277.962	449.267	7.096	15.035	0.141	0.298	+	+
28	5	0.2	E	D	D	268.768	65.560	9.206	2.240	0.183	0.044	+	+
29	5	0.2	D	E	E	324.648	245.296	7.011	5.957	0.139	0.118	+	+
30	5	0.2	D	E	D	355.883	480.126	11.714	21.458	0.232	0.426	+	+
31	5	0.2	D	D	E	425.563	185.127	10.990	6.531	0.218	0.130	+	+
32	5	0.2	D	D	D	411.887	17.079	13.616	0.755	0.270	0.015	+	+
33	5	0.5	E	E	E	68.106	318.758	4.358	20.117	0.086	0.399	+	+
34	5	0.5	E	E	D	68.472	343.764	4.791	24.807	0.095	0.492	+	+
35	5	0.5	E	D	E	84.713	385.737	4.343	22.401	0.086	0.444	+	+
36	5	0.5	E	D	D	84.749	183.946	4.588	6.351	0.091	0.126	+	+

37	5	0.5	D	E	E	110.307	75.216	6.988	12.061	0.139	0.239	+	+
38	5	0.5	D	E	D	108.920	249.056	4.888	10.371	0.097	0.206	+	+
39	5	0.5	D	D	E	152.321	642.916	6.822	42.633	0.135	0.845	+	+
40	5	0.5	D	D	D	138.125	68.564	6.745	2.312	0.134	0.046	+	+
41	5	0.8	E	E	E	51.259	248.742	2.608	12.310	0.052	0.244	+	+
42	5	0.8	E	E	D	52.854	356.377	2.845	19.096	0.056	0.379	+	+
43	5	0.8	E	D	E	71.906	375.986	3.683	18.463	0.073	0.366	+	+
44	5	0.8	E	D	D	69.148	-1.879	4.015	5.013	0.080	0.099	+	-
45	5	0.8	D	E	E	94.290	216.689	3.928	16.827	0.078	0.334	+	+
46	5	0.8	D	E	D	83.629	243.891	3.081	13.676	0.061	0.271	+	+
47	5	0.8	D	D	E	110.420	88.945	3.803	9.429	0.075	0.187	+	+
48	5	0.8	D	D	D	103.648	250.897	5.462	11.824	0.108	0.234	+	+

						No idle							
						Δ		σ		conf		sign	
No	NP	TI	PM	MC	PT	CT	Tar	CT	Tar	CT	Tar	CT	Tar
1	2	0.2	E	E	E	0.906	-2.076	1.983	0.144	0.039	0.003	+	-
2	2	0.2	E	E	D	1.405	477.495	1.137	37.975	0.023	0.753	+	+
3	2	0.2	E	D	E	-1.411	-411.660	1.521	7.761	0.030	0.154	-	-
4	2	0.2	E	D	D	-0.004	-15.044	1.905	11.147	0.038	0.221	-	-
5	2	0.2	D	E	E	-1.031	-27.560	1.419	0.738	0.028	0.015	-	-
6	2	0.2	D	E	D	-8.561	244.736	1.507	15.430	0.030	0.306	-	+
7	2	0.2	D	D	E	0.898	20.351	0.952	4.111	0.019	0.082	+	+
8	2	0.2	D	D	D	0.353	13.870	1.898	5.708	0.038	0.113	+	+
9	2	0.5	E	E	E	11.663	150.951	1.313	7.264	0.026	0.144	+	+
10	2	0.5	E	E	D	5.845	191.168	2.602	25.439	0.052	0.504	+	+
11	2	0.5	E	D	E	11.567	27.761	1.668	10.277	0.033	0.204	+	+
12	2	0.5	E	D	D	-2.668	6.493	2.368	5.682	0.047	0.113	-	+
13	2	0.5	D	E	E	33.461	161.687	2.329	4.806	0.046	0.095	+	+
14	2	0.5	D	E	D	-8.051	288.997	1.098	11.937	0.022	0.237	-	+
15	2	0.5	D	D	E	45.667	178.652	2.415	13.231	0.048	0.262	+	+
16	2	0.5	D	D	D	-5.182	82.762	1.267	7.296	0.025	0.145	-	+
17	2	0.8	E	E	E	14.691	59.368	1.495	5.023	0.030	0.100	+	+
18	2	0.8	E	E	D	35.285	101.637	1.424	12.776	0.028	0.253	+	+
19	2	0.8	E	D	E	14.228	59.218	1.606	6.352	0.032	0.126	+	+
20	2	0.8	E	D	D	-0.737	72.226	2.081	2.534	0.041	0.050	-	+
21	2	0.8	D	E	E	22.242	93.853	2.654	10.054	0.053	0.199	+	+
22	2	0.8	D	E	D	9.440	78.538	2.374	9.583	0.047	0.190	+	+
23	2	0.8	D	D	E	94.593	12.677	3.725	8.860	0.074	0.176	+	+
24	2	0.8	D	D	D	4.976	-378.368	1.662	12.831	0.033	0.254	+	-
25	5	0.2	E	E	E	4.284	-104.568	1.562	3.679	0.031	0.073	+	-
26	5	0.2	E	E	D	4.080	262.491	1.061	22.132	0.021	0.439	+	+
27	5	0.2	E	D	E	4.813	404.274	1.645	36.229	0.033	0.718	+	+
28	5	0.2	E	D	D	0.322	81.355	1.629	1.437	0.032	0.029	+	+
29	5	0.2	D	E	E	-1.122	102.847	2.012	3.050	0.040	0.060	-	+
30	5	0.2	D	E	D	0.981	118.316	2.141	18.472	0.042	0.366	+	+
31	5	0.2	D	D	E	1.094	138.056	2.271	7.264	0.045	0.144	+	+
32	5	0.2	D	D	D	1.860	24.414	1.128	1.131	0.022	0.022	+	+
33	5	0.5	E	E	E	8.194	64.105	2.685	11.658	0.053	0.231	+	+
34	5	0.5	E	E	D	144.088	352.753	7.346	32.536	0.146	0.645	+	+
35	5	0.5	E	D	E	110.181	608.445	5.401	30.575	0.107	0.606	+	+
36	5	0.5	E	D	D	30.019	148.366	3.094	5.050	0.061	0.100	+	+
37	5	0.5	D	E	E	20.968	202.991	2.436	16.135	0.048	0.320	+	+
38	5	0.5	D	E	D	6.785	135.475	2.903	9.870	0.058	0.196	+	+
39	5	0.5	D	D	E	65.456	535.179	5.011	30.836	0.099	0.611	+	+

40	5	0.5	D	D	D	-3.677	130.738	3.668	4.942	0.073	0.098	-	+
41	5	0.8	E	E	E	286.767	57.811	9.098	11.628	0.180	0.231	+	+
42	5	0.8	E	E	D	328.754	429.082	11.672	20.792	0.231	0.412	+	+
43	5	0.8	E	D	E	359.940	322.255	13.572	22.144	0.269	0.439	+	+
44	5	0.8	E	D	D	335.556	246.701	11.850	12.883	0.235	0.255	+	+
45	5	0.8	D	E	E	246.575	138.287	7.216	17.002	0.143	0.337	+	+
46	5	0.8	D	E	D	283.582	275.418	7.965	15.841	0.158	0.314	+	+
47	5	0.8	D	D	E	300.328	379.363	8.433	23.380	0.167	0.464	+	+
48	5	0.8	D	D	D	306.555	43.310	7.710	3.095	0.153	0.061	+	+

b) Comparison of approach using the dynamic weight with approach using the static weight

						Static							
						Δ		σ		conf		sign	
No	NP	TI	PM	MC	PT	CT	Tar	CT	Tar	CT	Tar	CT	Tar
1	2	0.2	E	E	E	7.031	247.496	1.219	4.787	0.024	0.095	+	+
2	2	0.2	E	E	D	5.635	425.993	1.451	17.466	0.029	0.346	+	+
3	2	0.2	E	D	E	-1.913	527.283	2.264	12.005	0.045	0.238	-	+
4	2	0.2	E	D	D	26.961	164.865	1.726	6.081	0.034	0.121	+	+
5	2	0.2	D	E	E	20.367	109.636	1.516	2.326	0.030	0.046	+	+
6	2	0.2	D	E	D	10.061	281.235	1.669	19.194	0.033	0.381	+	+
7	2	0.2	D	D	E	-2.469	94.983	1.429	2.774	0.028	0.055	-	+
8	2	0.2	D	D	D	9.622	202.149	2.169	4.624	0.043	0.092	+	+
9	2	0.5	E	E	E	1.763	45.972	1.041	2.677	0.021	0.053	+	+
10	2	0.5	E	E	D	-0.726	78.033	1.278	9.420	0.025	0.187	-	+
11	2	0.5	E	D	E	-4.902	284.857	1.480	9.369	0.029	0.186	-	+
12	2	0.5	E	D	D	4.800	59.998	0.958	2.920	0.019	0.058	+	+
13	2	0.5	D	E	E	-6.726	117.521	0.978	2.013	0.019	0.040	-	+
14	2	0.5	D	E	D	-6.139	82.195	1.450	9.025	0.029	0.179	-	+
15	2	0.5	D	D	E	11.786	12.161	1.506	8.625	0.030	0.171	-	+
16	2	0.5	D	D	D	0.185	60.612	1.974	4.607	0.039	0.091	+	+
17	2	0.8	E	E	E	-0.870	31.985	1.429	2.872	0.028	0.057	-	+
18	2	0.8	E	E	D	-5.564	27.528	0.972	3.975	0.019	0.079	-	+
19	2	0.8	E	D	E	8.114	177.794	0.971	5.912	0.019	0.117	+	+
20	2	0.8	E	D	D	4.432	32.056	1.295	2.384	0.026	0.047	+	+
21	2	0.8	D	E	E	-0.469	64.722	1.368	3.821	0.027	0.076	-	+
22	2	0.8	D	E	D	0.677	129.158	0.814	6.385	0.016	0.127	+	+
23	2	0.8	D	D	E	-7.644	83.472	2.333	6.542	0.046	0.130	-	+
24	2	0.8	D	D	D	0.844	660.605	0.893	11.670	0.018	0.231	+	+
25	5	0.2	E	E	E	19.872	180.955	2.963	3.570	0.059	0.071	+	+
26	5	0.2	E	E	D	20.617	319.618	2.493	12.535	0.049	0.249	+	+
27	5	0.2	E	D	E	21.025	411.654	2.133	21.424	0.042	0.425	+	+
28	5	0.2	E	D	D	22.836	187.705	3.224	3.462	0.064	0.069	+	+
29	5	0.2	D	E	E	26.449	183.125	3.257	4.280	0.065	0.085	+	+
30	5	0.2	D	E	D	25.921	221.363	4.955	13.039	0.098	0.259	+	+
31	5	0.2	D	D	E	24.566	50.170	4.110	3.750	0.082	0.074	+	+
32	5	0.2	D	D	D	24.148	83.945	6.607	2.186	0.131	0.043	+	+
33	5	0.5	E	E	E	-2.964	65.862	2.273	11.145	0.045	0.221	-	+
34	5	0.5	E	E	D	0.672	228.914	3.488	19.782	0.069	0.392	+	+

35	5	0.5	E	D	E	-2.229	124.971	1.465	15.447	0.029	0.306	-	+
36	5	0.5	E	D	D	1.293	298.202	1.100	9.587	0.022	0.190	+	+
37	5	0.5	D	E	E	-3.118	123.671	1.384	7.897	0.027	0.157	-	+
38	5	0.5	D	E	D	-4.228	125.090	2.088	6.499	0.041	0.129	-	+
39	5	0.5	D	D	E	-1.023	318.133	2.086	28.408	0.041	0.563	-	+
40	5	0.5	D	D	D	1.089	41.293	2.918	3.221	0.058	0.064	+	+
41	5	0.8	E	E	E	-7.391	277.352	3.085	13.704	0.061	0.272	-	+
42	5	0.8	E	E	D	-7.383	46.935	4.266	8.655	0.085	0.172	-	+
43	5	0.8	E	D	E	-4.759	127.930	5.883	10.369	0.117	0.206	-	+
44	5	0.8	E	D	D	-0.206	218.930	5.010	9.926	0.099	0.197	-	+
45	5	0.8	D	E	E	-6.140	325.471	4.109	5.354	0.081	0.106	-	+
46	5	0.8	D	E	D	5.309	116.054	4.535	8.235	0.090	0.163	+	+
47	5	0.8	D	D	E	10.671	264.873	4.634	14.223	0.092	0.282	+	+
48	5	0.8	D	D	D	3.311	132.129	4.538	3.945	0.090	0.078	+	+

APPENDIX B

PAIRED-T TEST FOR CHAPTER V

The production characteristics and settings used in paired-t test are as follows:

No.	Factor	Setting		
1	Number of Products (NP)	2		
	Number of Products (NP)	5		
2	Product Mix (PM)	Equal(E)	2 products	(0.5,0.5)
	Product Mix (PM)	Equal(E)	5 products	(0.2,0.2,0.2,0.2,0.2)
	Product Mix (PM)	Different(D)	2 products	(0.2,0.8)
	Product Mix (PM)	Different(D)	5 products	(0.1,0.1,0.1,0.35,0.35)
3	Machine Capacity by Product (MC)	Equal(E)	2 products	(5,5)
	Machine Capacity by Product (MC)	Equal(E)	5 products	(5,5,5,5,5)
	Machine Capacity by Product (MC)	Different(D)	2 products	(3,7)
	Machine Capacity by Product (MC)	Different(D)	5 products	(3,4,5,6,7)
4	Processing Time by Product (PT)	Equal(E)	2 products	(25,25)
	Processing Time by Product (PT)	Equal(E)	5 products	(25,25,25,25,25)
	Processing Time by Product (PT)	Different(D)	2 products	(10,40)
	Processing Time by Product (PT)	Different(D)	5 products	(10,20,25,30,40)
5	Traffic Intensity (TI)	0.2		
	Traffic Intensity (TI)	0.5		
	Traffic Intensity (TI)	0.8		

$\varDelta$ = The mean of the normalized differences for cycle time and tardiness obtained by 10 replications of NACH-SUE and the other strategies that the column belongs to. For example, if X~MBS-SUE and Y~NACH-SUE then,

$$\varDelta = \frac{1}{10}\sum_{i=1}^{10}(X_i - Y_i)$$

σ = The standard deviation of the replication differences

conf = The half-width of the 95% confidence interval of the replication differences

sign = + if there is a significant performance difference observed with NACH-SUE
- if there is not a significant performance difference observed with NACH-SUE

a) Comparison of NACH-SUE with the other benchmarks

						MBS-SUE					
						Δ			σ		
No	NP	TI	PM	MC	PT	CT	Ear	Tar	CT	Ear	Tar
1	2	0.2	E	E	E	1.694	30.940	51.662	0.756	7.522	1.840
2	2	0.2	E	E	D	2.197	499.082	241.981	1.040	51.796	21.008
3	2	0.2	E	D	E	0.992	384.215	85.213	1.074	27.376	27.945
4	2	0.2	E	D	D	1.251	-49.645	134.874	1.128	6.231	8.404
5	2	0.2	D	E	E	-0.274	-151.564	66.660	1.427	15.533	2.278
6	2	0.2	D	E	D	-1.483	-18.686	516.348	1.144	6.210	22.860
7	2	0.2	D	D	E	0.253	108.307	34.654	1.355	13.794	5.634
8	2	0.2	D	D	D	0.613	1258.762	59.228	1.598	44.125	11.230
9	2	0.5	E	E	E	8.740	17.968	84.850	0.937	1.140	4.296
10	2	0.5	E	E	D	6.800	53.145	83.198	1.751	3.884	17.513
11	2	0.5	E	D	E	12.096	264.145	132.797	1.683	43.690	16.737
12	2	0.5	E	D	D	-3.204	-47.561	21.320	1.524	3.255	6.447
13	2	0.5	D	E	E	9.862	72.655	139.054	1.956	1.727	3.526
14	2	0.5	D	E	D	-1.021	-24.139	311.942	2.006	4.086	13.730
15	2	0.5	D	D	E	27.444	102.376	89.372	1.647	9.895	11.152
16	2	0.5	D	D	D	-4.952	1180.466	44.644	2.034	61.806	3.833
17	2	0.8	E	E	E	13.115	8.468	19.084	1.855	0.302	1.751
18	2	0.8	E	E	D	16.569	44.203	74.690	1.573	5.655	9.127
19	2	0.8	E	D	E	44.198	289.883	166.582	3.131	27.885	15.494
20	2	0.8	E	D	D	-3.171	272.792	14.106	1.730	41.099	2.524
21	2	0.8	D	E	E	22.439	6.633	64.464	1.959	0.270	6.889
22	2	0.8	D	E	D	8.716	8.084	149.935	1.408	5.111	11.774
23	2	0.8	D	D	E	45.197	161.661	99.679	2.856	8.835	11.275
24	2	0.8	D	D	D	5.280	1206.148	140.852	1.695	54.373	36.661
25	5	0.2	E	E	E	0.670	258.874	37.207	2.062	10.144	5.638
26	5	0.2	E	E	D	2.102	587.404	333.345	1.800	37.779	23.089
27	5	0.2	E	D	E	1.966	523.848	544.582	1.486	22.658	46.827
28	5	0.2	E	D	D	0.158	937.674	91.350	2.092	54.067	3.154
29	5	0.2	D	E	E	-1.337	288.397	70.116	1.783	14.980	7.626
30	5	0.2	D	E	D	1.765	881.529	293.448	1.573	61.093	18.367
31	5	0.2	D	D	E	0.939	280.918	92.164	1.469	19.368	6.140
32	5	0.2	D	D	D	0.638	728.924	44.194	1.764	38.971	1.934
33	5	0.5	E	E	E	6.855	560.848	202.943	3.092	27.804	12.606
34	5	0.5	E	E	D	3.451	458.609	403.160	3.434	25.034	26.691
35	5	0.5	E	D	E	23.320	316.261	393.357	2.181	21.654	30.699
36	5	0.5	E	D	D	9.474	516.048	164.589	2.686	31.166	5.524

37	5	0.5	D	E	E	1.363	205.356	158.811	4.114	29.528	12.523
38	5	0.5	D	E	D	12.786	718.375	197.668	3.165	30.814	8.757
39	5	0.5	D	D	E	40.935	113.731	560.952	4.783	11.350	45.537
40	5	0.5	D	D	D	10.148	468.897	8.967	3.757	35.880	0.866
41	5	0.8	E	E	E	37.001	164.878	174.818	2.721	10.265	18.432
42	5	0.8	E	E	D	32.614	400.001	296.657	2.403	24.533	22.611
43	5	0.8	E	D	E	47.810	278.137	236.315	3.774	23.198	19.327
44	5	0.8	E	D	D	39.376	472.823	84.095	2.915	15.680	6.464
45	5	0.8	D	E	E	36.776	147.903	237.871	2.483	10.683	23.090
46	5	0.8	D	E	D	63.875	-368.758	87.796	4.000	18.223	5.473
47	5	0.8	D	D	E	35.040	12.482	60.043	2.753	3.581	11.831
48	5	0.8	D	D	D	48.377	404.021	152.033	3.720	25.964	6.281

MBS-SUE

No	NP	TI	PM	MC	PT	conf CT	conf Ear	conf Tar	sign CT	sign Ear	sign Tar
1	2	0.2	E	E	E	0.015	0.149	0.036	+	+	+
2	2	0.2	E	E	D	0.021	1.027	0.417	+	+	+
3	2	0.2	E	D	E	0.021	0.543	0.554	+	+	+
4	2	0.2	E	D	D	0.022	0.124	0.167	+	-	+
5	2	0.2	D	E	E	0.028	0.308	0.045	-	-	+
6	2	0.2	D	E	D	0.023	0.123	0.453	-	-	+
7	2	0.2	D	D	E	0.027	0.274	0.112	+	+	+
8	2	0.2	D	D	D	0.032	0.875	0.223	+	+	+
9	2	0.5	E	E	E	0.019	0.023	0.085	+	+	+
10	2	0.5	E	E	D	0.035	0.077	0.347	+	+	+
11	2	0.5	E	D	E	0.033	0.866	0.332	+	+	+
12	2	0.5	E	D	D	0.030	0.065	0.128	-	-	+
13	2	0.5	D	E	E	0.039	0.034	0.070	+	+	+
14	2	0.5	D	E	D	0.040	0.081	0.272	-	-	+
15	2	0.5	D	D	E	0.033	0.196	0.221	+	+	+
16	2	0.5	D	D	D	0.040	1.226	0.076	-	+	+
17	2	0.8	E	E	E	0.037	0.006	0.035	+	+	+
18	2	0.8	E	E	D	0.031	0.112	0.181	+	+	+
19	2	0.8	E	D	E	0.062	0.553	0.307	+	+	+
20	2	0.8	E	D	D	0.034	0.815	0.050	-	+	+
21	2	0.8	D	E	E	0.039	0.005	0.137	+	+	+
22	2	0.8	D	E	D	0.028	0.101	0.233	+	+	+
23	2	0.8	D	D	E	0.057	0.175	0.224	+	+	+
24	2	0.8	D	D	D	0.034	1.078	0.727	+	+	+
25	5	0.2	E	E	E	0.041	0.201	0.112	+	+	+
26	5	0.2	E	E	D	0.036	0.749	0.458	+	+	+
27	5	0.2	E	D	E	0.029	0.449	0.929	+	+	+
28	5	0.2	E	D	D	0.041	1.072	0.063	+	+	+
29	5	0.2	D	E	E	0.035	0.297	0.151	-	+	+
30	5	0.2	D	E	D	0.031	1.211	0.364	+	+	+
31	5	0.2	D	D	E	0.029	0.384	0.122	+	+	+
32	5	0.2	D	D	D	0.035	0.773	0.038	+	+	+
33	5	0.5	E	E	E	0.061	0.551	0.250	+	+	+
34	5	0.5	E	E	D	0.068	0.496	0.529	+	+	+
35	5	0.5	E	D	E	0.043	0.429	0.609	+	+	+
36	5	0.5	E	D	D	0.053	0.618	0.110	+	+	+

37	5	0.5	D	E	E	0.082	0.586	0.248	+	+	+
38	5	0.5	D	E	D	0.063	0.611	0.174	+	+	+
39	5	0.5	D	D	E	0.095	0.225	0.903	+	+	+
40	5	0.5	D	D	D	0.074	0.711	0.017	+	+	+
41	5	0.8	E	E	E	0.054	0.204	0.366	+	+	+
42	5	0.8	E	E	D	0.048	0.486	0.448	+	+	+
43	5	0.8	E	D	E	0.075	0.460	0.383	+	+	+
44	5	0.8	E	D	D	0.058	0.311	0.128	+	+	+
45	5	0.8	D	E	E	0.049	0.212	0.458	+	+	+
46	5	0.8	D	E	D	0.079	0.361	0.109	+	-	+
47	5	0.8	D	D	E	0.055	0.071	0.235	+	+	+
48	5	0.8	D	D	D	0.074	0.515	0.125	+	+	+

Full batch

						Δ			σ		
No	**NP**	**TI**	**PM**	**MC**	**PT**	**CT**	**Ear**	**Tar**	**CT**	**Ear**	**Tar**
1	2	0.2	E	E	E	91.717	15.461	136.913	2.238	5.232	4.136
2	2	0.2	E	E	D	116.262	583.702	328.989	3.052	42.503	26.918
3	2	0.2	E	D	E	115.254	348.952	224.703	4.196	41.142	19.233
4	2	0.2	E	D	D	117.115	-51.847	286.716	3.066	5.741	12.281
5	2	0.2	D	E	E	136.296	-32.949	72.197	5.485	18.682	2.438
6	2	0.2	D	E	D	142.900	-15.030	571.669	4.771	7.691	26.885
7	2	0.2	D	D	E	213.342	107.005	129.521	5.661	15.126	10.015
8	2	0.2	D	D	D	200.177	1218.763	243.050	4.216	44.763	14.301
9	2	0.5	E	E	E	34.044	7.896	196.136	2.216	0.736	8.350
10	2	0.5	E	E	D	32.747	55.399	150.273	2.283	5.174	16.248
11	2	0.5	E	D	E	40.113	249.479	347.558	2.834	22.398	20.254
12	2	0.5	E	D	D	31.927	-54.134	181.595	2.210	5.871	7.846
13	2	0.5	D	E	E	52.008	90.773	168.335	1.977	2.351	6.904
14	2	0.5	D	E	D	48.485	-22.281	360.256	2.553	4.775	16.665
15	2	0.5	D	D	E	79.602	143.402	232.542	3.066	16.089	17.101
16	2	0.5	D	D	D	70.711	1245.238	150.176	3.726	39.850	8.609
17	2	0.8	E	E	E	20.394	38.876	32.424	1.261	1.412	6.748
18	2	0.8	E	E	D	24.753	50.019	124.796	2.083	4.037	10.975
19	2	0.8	E	D	E	44.461	302.473	187.099	2.765	38.474	6.517
20	2	0.8	E	D	D	12.507	236.027	80.836	1.780	39.589	5.113
21	2	0.8	D	E	E	38.405	31.717	79.227	2.146	1.021	7.453
22	2	0.8	D	E	D	31.951	87.463	217.119	1.903	6.808	11.336
23	2	0.8	D	D	E	56.853	171.173	185.811	2.245	11.949	13.775
24	2	0.8	D	D	D	50.269	1277.582	335.267	2.157	60.762	25.940
25	5	0.2	E	E	E	237.545	362.040	102.157	10.272	16.432	5.448
26	5	0.2	E	E	D	243.920	595.632	914.191	8.634	32.103	30.860
27	5	0.2	E	D	E	279.340	677.665	872.546	9.183	46.540	34.809
28	5	0.2	E	D	D	265.090	1410.119	296.221	9.018	71.233	10.165
29	5	0.2	D	E	E	324.181	362.033	179.278	11.017	15.825	10.118
30	5	0.2	D	E	D	369.012	1003.862	379.754	9.785	35.528	26.601
31	5	0.2	D	D	E	439.034	344.056	175.065	15.528	13.656	9.195
32	5	0.2	D	D	D	410.679	951.864	96.655	13.761	57.382	2.827
33	5	0.5	E	E	E	72.255	570.628	488.668	3.632	17.747	21.626
34	5	0.5	E	E	D	67.998	477.261	459.254	2.937	24.278	28.925
35	5	0.5	E	D	E	87.148	277.533	437.380	2.860	22.261	31.155
36	5	0.5	E	D	D	85.938	532.310	962.312	3.551	23.387	21.817

37	5	0.5	D	E	E	91.279	593.585	264.975	5.010	37.738	14.906
38	5	0.5	D	E	D	114.668	759.810	232.785	6.048	42.617	12.157
39	5	0.5	D	D	E	145.786	154.108	613.761	5.759	9.412	40.676
40	5	0.5	D	D	D	143.939	540.879	109.935	7.206	33.450	3.862
41	5	0.8	E	E	E	52.910	193.686	196.105	2.002	10.628	12.361
42	5	0.8	E	E	D	54.637	470.722	335.350	4.127	22.799	26.000
43	5	0.8	E	D	E	67.266	331.321	310.053	3.380	17.494	12.620
44	5	0.8	E	D	D	67.114	624.688	190.400	3.555	18.154	9.423
45	5	0.8	D	E	E	72.678	167.316	399.204	2.974	11.196	19.390
46	5	0.8	D	E	D	96.360	-303.764	363.723	4.772	22.063	16.650
47	5	0.8	D	D	E	101.962	57.880	147.769	4.266	4.192	21.384
48	5	0.8	D	D	D	103.656	445.793	279.519	5.851	16.707	9.728

Full batch

						conf			sign		
No	**NP**	**TI**	**PM**	**MC**	**PT**	**CT**	**Ear**	**Tar**	**CT**	**Ear**	**Tar**
1	2	0.2	E	E	E	0.044	0.104	0.082	+	+	+
2	2	0.2	E	E	D	0.061	0.843	0.534	+	+	+
3	2	0.2	E	D	E	0.083	0.816	0.381	+	+	+
4	2	0.2	E	D	D	0.061	0.114	0.244	+	-	+
5	2	0.2	D	E	E	0.109	0.370	0.048	+	-	+
6	2	0.2	D	E	D	0.095	0.153	0.533	+	-	+
7	2	0.2	D	D	E	0.112	0.300	0.199	+	+	+
8	2	0.2	D	D	D	0.084	0.888	0.284	+	+	+
9	2	0.5	E	E	E	0.044	0.015	0.166	+	+	+
10	2	0.5	E	E	D	0.045	0.103	0.322	+	+	+
11	2	0.5	E	D	E	0.056	0.444	0.402	+	+	+
12	2	0.5	E	D	D	0.044	0.116	0.156	+	-	+
13	2	0.5	D	E	E	0.039	0.047	0.137	+	+	+
14	2	0.5	D	E	D	0.051	0.095	0.330	+	-	+
15	2	0.5	D	D	E	0.061	0.319	0.339	+	+	+
16	2	0.5	D	D	D	0.074	0.790	0.171	+	+	+
17	2	0.8	E	E	E	0.025	0.028	0.134	+	+	+
18	2	0.8	E	E	D	0.041	0.080	0.218	+	+	+
19	2	0.8	E	D	E	0.055	0.763	0.129	+	+	+
20	2	0.8	E	D	D	0.035	0.785	0.101	+	+	+
21	2	0.8	D	E	E	0.043	0.020	0.148	+	+	+
22	2	0.8	D	E	D	0.038	0.135	0.225	+	+	+
23	2	0.8	D	D	E	0.045	0.237	0.273	+	+	+
24	2	0.8	D	D	D	0.043	1.205	0.514	+	+	+
25	5	0.2	E	E	E	0.204	0.326	0.108	+	+	+
26	5	0.2	E	E	D	0.171	0.637	0.612	+	+	+
27	5	0.2	E	D	E	0.182	0.923	0.690	+	+	+
28	5	0.2	E	D	D	0.179	1.413	0.202	+	+	+
29	5	0.2	D	E	E	0.218	0.314	0.201	+	+	+
30	5	0.2	D	E	D	0.194	0.705	0.527	+	+	+
31	5	0.2	D	D	E	0.308	0.271	0.182	+	+	+
32	5	0.2	D	D	D	0.273	1.138	0.056	+	+	+
33	5	0.5	E	E	E	0.072	0.352	0.429	+	+	+
34	5	0.5	E	E	D	0.058	0.481	0.574	+	+	+
35	5	0.5	E	D	E	0.057	0.441	0.618	+	+	+
36	5	0.5	E	D	D	0.070	0.464	0.433	+	+	+
37	5	0.5	D	E	E	0.099	0.748	0.296	+	+	+

38	5	0.5	D	E	D	0.120	0.845	0.241	+	+	+
39	5	0.5	D	D	E	0.114	0.187	0.807	+	+	+
40	5	0.5	D	D	D	0.143	0.663	0.077	+	+	+
41	5	0.8	E	E	E	0.040	0.211	0.245	+	+	+
42	5	0.8	E	E	D	0.082	0.452	0.516	+	+	+
43	5	0.8	E	D	E	0.067	0.347	0.250	+	+	+
44	5	0.8	E	D	D	0.070	0.360	0.187	+	+	+
45	5	0.8	D	E	E	0.059	0.222	0.385	+	+	+
46	5	0.8	D	E	D	0.095	0.438	0.330	+	-	+
47	5	0.8	D	D	E	0.085	0.083	0.424	+	+	+
48	5	0.8	D	D	D	0.116	0.331	0.193	+	+	+

No idle

No	NP	TI	PM	MC	PT	Δ CT	Δ Ear	Δ Tar	σ CT	σ Ear	σ Tar
1	2	0.2	E	E	E	1.365	24.313	50.746	1.564	5.664	1.147
2	2	0.2	E	E	D	1.819	506.722	232.078	1.361	35.247	36.358
3	2	0.2	E	D	E	1.236	407.943	87.129	1.004	18.702	24.442
4	2	0.2	E	D	D	1.186	-51.479	122.608	1.846	5.140	13.300
5	2	0.2	D	E	E	-0.921	-157.388	66.909	1.818	11.849	2.372
6	2	0.2	D	E	D	-0.820	-24.427	504.916	1.611	4.922	23.433
7	2	0.2	D	D	E	0.614	105.839	35.816	1.094	10.402	4.942
8	2	0.2	D	D	D	1.194	1206.990	62.798	1.318	46.371	8.602
9	2	0.5	E	E	E	9.710	16.662	92.269	2.011	0.673	7.025
10	2	0.5	E	E	D	6.949	47.702	78.203	1.952	4.249	18.602
11	2	0.5	E	D	E	21.842	334.471	150.215	1.744	23.845	11.804
12	2	0.5	E	D	D	-2.844	-47.602	25.480	1.753	5.265	3.027
13	2	0.5	D	E	E	28.578	91.008	209.971	1.259	2.743	9.027
14	2	0.5	D	E	D	-0.380	-22.034	310.698	1.679	5.021	14.777
15	2	0.5	D	D	E	46.166	102.330	121.656	2.813	17.316	12.331
16	2	0.5	D	D	D	-5.111	1173.064	45.660	1.493	47.888	4.649
17	2	0.8	E	E	E	21.676	13.942	58.716	2.122	0.693	8.693
18	2	0.8	E	E	D	29.004	45.421	103.995	1.199	3.824	8.670
19	2	0.8	E	D	E	84.439	362.773	204.358	3.864	22.656	12.313
20	2	0.8	E	D	D	17.252	306.933	24.362	2.012	26.301	2.432
21	2	0.8	D	E	E	42.074	6.940	78.175	2.240	0.253	8.865
22	2	0.8	D	E	D	8.501	11.303	162.996	1.530	3.551	8.877
23	2	0.8	D	D	E	99.639	192.812	217.895	3.874	15.796	13.496
24	2	0.8	D	D	D	4.647	1207.661	134.175	1.804	27.901	24.642
25	5	0.2	E	E	E	2.720	267.656	39.848	1.640	11.037	4.457
26	5	0.2	E	E	D	2.153	608.744	332.419	1.959	38.409	38.748
27	5	0.2	E	D	E	2.486	489.801	604.413	1.945	38.333	33.074
28	5	0.2	E	D	D	-0.321	969.421	96.369	2.019	48.321	1.875
29	5	0.2	D	E	E	-0.228	290.423	69.841	1.735	16.862	6.108
30	5	0.2	D	E	D	1.257	900.568	313.341	1.679	64.284	15.826
31	5	0.2	D	D	E	2.253	297.700	95.285	2.272	14.004	8.421
32	5	0.2	D	D	D	1.228	751.948	44.927	1.725	38.942	1.248
33	5	0.5	E	E	E	12.500	590.760	229.130	2.812	28.891	19.290
34	5	0.5	E	E	D	149.477	582.580	711.387	6.462	27.919	20.736
35	5	0.5	E	D	E	117.239	353.729	569.097	5.748	16.873	34.511
36	5	0.5	E	D	D	28.973	437.866	244.971	3.705	16.781	8.391

37	5	0.5	D	E	E	12.461	166.855	249.902	3.525	28.290	10.243
38	5	0.5	D	E	D	30.374	694.152	270.730	2.278	48.264	10.283
39	5	0.5	D	D	E	72.450	108.578	862.644	3.626	8.072	47.550
40	5	0.5	D	D	D	9.975	454.922	8.462	3.889	33.095	0.998
41	5	0.8	E	E	E	292.079	59.760	592.828	6.875	8.487	22.192
42	5	0.8	E	E	D	334.226	449.266	435.593	10.373	20.720	23.182
43	5	0.8	E	D	E	368.282	300.225	416.135	11.806	20.550	18.129
44	5	0.8	E	D	D	344.387	488.510	237.803	11.028	22.501	10.455
45	5	0.8	D	E	E	237.187	206.188	513.464	9.895	14.721	21.894
46	5	0.8	D	E	D	290.902	-333.372	525.715	10.041	23.110	19.355
47	5	0.8	D	D	E	321.110	25.479	227.280	14.854	4.769	26.709
48	5	0.8	D	D	D	319.574	529.245	215.147	10.188	26.179	6.987

No idle

No	NP	TI	PM	MC	PT	conf CT	conf Ear	conf Tar	sign CT	sign Ear	sign Tar
1	2	0.2	E	E	E	0.031	0.112	0.023	+	+	+
2	2	0.2	E	E	D	0.027	0.699	0.721	+	+	+
3	2	0.2	E	D	E	0.020	0.371	0.485	+	+	+
4	2	0.2	E	D	D	0.037	0.102	0.264	+	-	+
5	2	0.2	D	E	E	0.036	0.235	0.047	-	-	+
6	2	0.2	D	E	D	0.032	0.098	0.465	-	-	+
7	2	0.2	D	D	E	0.022	0.206	0.098	+	+	+
8	2	0.2	D	D	D	0.026	0.920	0.171	+	+	+
9	2	0.5	E	E	E	0.040	0.013	0.139	+	+	+
10	2	0.5	E	E	D	0.039	0.084	0.369	+	+	+
11	2	0.5	E	D	E	0.035	0.473	0.234	+	+	+
12	2	0.5	E	D	D	0.035	0.104	0.060	-	-	+
13	2	0.5	D	E	E	0.025	0.054	0.179	+	+	+
14	2	0.5	D	E	D	0.033	0.100	0.293	-	-	+
15	2	0.5	D	D	E	0.056	0.343	0.245	+	+	+
16	2	0.5	D	D	D	0.030	0.950	0.092	-	+	+
17	2	0.8	E	E	E	0.042	0.014	0.172	+	+	+
18	2	0.8	E	E	D	0.024	0.076	0.172	+	+	+
19	2	0.8	E	D	E	0.077	0.449	0.244	+	+	+
20	2	0.8	E	D	D	0.040	0.522	0.048	+	+	+
21	2	0.8	D	E	E	0.044	0.005	0.176	+	+	+
22	2	0.8	D	E	D	0.030	0.070	0.176	+	+	+
23	2	0.8	D	D	E	0.077	0.313	0.268	+	+	+
24	2	0.8	D	D	D	0.036	0.553	0.489	+	+	+
25	5	0.2	E	E	E	0.033	0.219	0.088	+	+	+
26	5	0.2	E	E	D	0.039	0.762	0.768	+	+	+
27	5	0.2	E	D	E	0.039	0.760	0.656	+	+	+
28	5	0.2	E	D	D	0.040	0.958	0.037	-	+	+
29	5	0.2	D	E	E	0.034	0.334	0.121	-	+	+
30	5	0.2	D	E	D	0.033	1.275	0.314	+	+	+
31	5	0.2	D	D	E	0.045	0.278	0.167	+	+	+
32	5	0.2	D	D	D	0.034	0.772	0.025	+	+	+
33	5	0.5	E	E	E	0.056	0.573	0.383	+	+	+
34	5	0.5	E	E	D	0.128	0.554	0.411	+	+	+
35	5	0.5	E	D	E	0.114	0.335	0.684	+	+	+
36	5	0.5	E	D	D	0.073	0.333	0.166	+	+	+

37	5	0.5	D	E	E	0.070	0.561	0.203	+	+	+
38	5	0.5	D	E	D	0.045	0.957	0.204	+	+	+
39	5	0.5	D	D	E	0.072	0.160	0.943	+	+	+
40	5	0.5	D	D	D	0.077	0.656	0.020	+	+	+
41	5	0.8	E	E	E	0.136	0.168	0.440	+	+	+
42	5	0.8	E	E	D	0.206	0.411	0.460	+	+	+
43	5	0.8	E	D	E	0.234	0.407	0.359	+	+	+
44	5	0.8	E	D	D	0.219	0.446	0.207	+	+	+
45	5	0.8	D	E	E	0.196	0.292	0.434	+	+	+
46	5	0.8	D	E	D	0.199	0.458	0.384	+	-	+
47	5	0.8	D	D	E	0.295	0.095	0.530	+	+	+
48	5	0.8	D	D	D	0.202	0.519	0.139	+	+	+

b) Comparison of approach using the dynamic weight with approach using the static weight

						Static					
						Δ			σ		
No	NP	TI	PM	MC	PT	CT	Ear	Tar	CT	Ear	Tar
1	2	0.2	E	E	E	5.856	125.985	204.250	1.151	5.667	5.288
2	2	0.2	E	E	D	-0.498	3287.706	266.769	0.946	101.956	10.988
3	2	0.2	E	D	E	4.233	275.626	121.017	1.789	30.116	15.761
4	2	0.2	E	D	D	27.395	113.348	79.660	1.882	4.340	8.782
5	2	0.2	D	E	E	21.150	82.341	62.406	2.396	6.372	2.245
6	2	0.2	D	E	D	3.645	5.799	83.748	1.729	2.227	10.723
7	2	0.2	D	D	E	-3.353	38.648	55.713	2.468	5.356	2.616
8	2	0.2	D	D	D	11.630	-723.577	82.228	2.212	19.375	6.541
9	2	0.5	E	E	E	2.373	13.880	46.900	1.192	0.729	4.685
10	2	0.5	E	E	D	-0.607	10.096	83.511	0.739	2.615	11.218
11	2	0.5	E	D	E	-5.323	203.510	79.027	0.817	17.433	9.285
12	2	0.5	E	D	D	4.155	55.463	39.005	0.611	1.981	5.479
13	2	0.5	D	E	E	-5.031	14.304	42.655	1.003	1.067	2.151
14	2	0.5	D	E	D	-3.303	10.129	57.483	0.861	4.298	9.936
15	2	0.5	D	D	E	11.947	32.945	54.727	1.172	4.316	9.226
16	2	0.5	D	D	D	1.068	-721.024	60.934	0.794	15.691	4.848
17	2	0.8	E	E	E	-2.969	25.032	23.260	1.041	0.819	2.804
18	2	0.8	E	E	D	-3.695	9.922	50.149	0.932	2.526	6.955
19	2	0.8	E	D	E	20.458	89.022	52.301	1.201	19.858	8.005
20	2	0.8	E	D	D	-0.353	115.804	57.581	0.964	15.373	2.625
21	2	0.8	D	E	E	-6.232	14.840	75.541	0.957	0.571	4.216
22	2	0.8	D	E	D	0.865	23.337	70.469	0.716	3.049	8.023
23	2	0.8	D	D	E	-8.535	54.447	5.051	1.737	9.309	9.007
24	2	0.8	D	D	D	1.098	128.666	107.634	0.975	29.794	20.400
25	5	0.2	E	E	E	21.818	85.335	77.030	3.321	6.435	6.238
26	5	0.2	E	E	D	20.147	29.070	245.536	2.931	20.042	13.843
27	5	0.2	E	D	E	20.606	176.444	259.504	2.888	20.218	22.276
28	5	0.2	E	D	D	23.536	139.122	94.724	2.190	28.739	5.027
29	5	0.2	D	E	E	27.922	25.914	90.591	4.928	7.730	4.613
30	5	0.2	D	E	D	19.954	75.399	107.592	3.585	34.654	17.615
31	5	0.2	D	D	E	18.749	31.094	63.865	3.329	12.277	4.415
32	5	0.2	D	D	D	24.024	275.945	50.395	5.184	24.140	1.235
33	5	0.5	E	E	E	-4.475	45.271	101.569	2.293	16.318	7.335
34	5	0.5	E	E	D	-1.231	38.864	88.521	2.940	12.015	21.723

35	5	0.5	E	D	E	-4.052	35.869	51.177	2.145	9.990	14.898
36	5	0.5	E	D	D	1.685	62.613	80.988	1.957	15.581	7.219
37	5	0.5	D	E	E	-9.789	84.393	92.692	2.194	17.130	6.430
38	5	0.5	D	E	D	11.646	124.992	91.617	2.258	21.939	8.922
39	5	0.5	D	D	E	-2.027	30.368	171.954	3.181	6.674	29.239
40	5	0.5	D	D	D	-6.942	15.800	102.168	2.665	18.612	3.087
41	5	0.8	E	E	E	-8.394	37.652	147.248	3.627	5.264	11.128
42	5	0.8	E	E	D	-6.602	19.301	21.652	3.965	14.355	9.525
43	5	0.8	E	D	E	-5.813	36.240	92.151	3.296	11.450	7.944
44	5	0.8	E	D	D	-3.074	85.783	106.460	3.278	13.198	8.197
45	5	0.8	D	E	E	-7.399	26.619	121.154	3.273	6.573	11.101
46	5	0.8	D	E	D	-4.785	47.179	31.099	4.807	7.299	13.760
47	5	0.8	D	D	E	6.030	131.505	268.789	5.097	4.934	13.407
48	5	0.8	D	D	D	-1.652	-0.763	50.047	4.837	15.714	5.212

						Static					
							conf			sign	
No	**NP**	**TI**	**PM**	**MC**	**PT**	**CT**	**Ear**	**Tar**	**CT**	**Ear**	**Tar**
1	2	0.2	E	E	E	0.023	0.112	0.105	+	+	+
2	2	0.2	E	E	D	0.019	2.022	0.218	-	+	+
3	2	0.2	E	D	E	0.035	0.597	0.313	+	+	+
4	2	0.2	E	D	D	0.037	0.086	0.174	+	+	+
5	2	0.2	D	E	E	0.048	0.126	0.045	+	+	+
6	2	0.2	D	E	D	0.034	0.044	0.213	+	+	+
7	2	0.2	D	D	E	0.049	0.106	0.052	-	+	+
8	2	0.2	D	D	D	0.044	0.384	0.130	+	-	+
9	2	0.5	E	E	E	0.024	0.014	0.093	+	+	+
10	2	0.5	E	E	D	0.015	0.052	0.222	-	+	+
11	2	0.5	E	D	E	0.016	0.346	0.184	-	+	+
12	2	0.5	E	D	D	0.012	0.039	0.109	+	+	+
13	2	0.5	D	E	E	0.020	0.021	0.043	-	+	+
14	2	0.5	D	E	D	0.017	0.085	0.197	-	+	+
15	2	0.5	D	D	E	0.023	0.086	0.183	-	+	+
16	2	0.5	D	D	D	0.016	0.311	0.096	+	-	+
17	2	0.8	E	E	E	0.021	0.016	0.056	-	+	+
18	2	0.8	E	E	D	0.018	0.050	0.138	-	+	+
19	2	0.8	E	D	E	0.024	0.394	0.159	-	+	+
20	2	0.8	E	D	D	0.019	0.305	0.052	-	+	+
21	2	0.8	D	E	E	0.019	0.011	0.084	-	+	+
22	2	0.8	D	E	D	0.014	0.060	0.159	+	+	+
23	2	0.8	D	D	E	0.034	0.185	0.179	-	+	+
24	2	0.8	D	D	D	0.019	0.591	0.405	+	+	+
25	5	0.2	E	E	E	0.066	0.128	0.124	+	+	+
26	5	0.2	E	E	D	0.058	0.397	0.274	+	+	+
27	5	0.2	E	D	E	0.057	0.401	0.442	+	+	+
28	5	0.2	E	D	D	0.043	0.570	0.100	+	+	+
29	5	0.2	D	E	E	0.098	0.153	0.091	+	+	+
30	5	0.2	D	E	D	0.071	0.687	0.349	+	+	+
31	5	0.2	D	D	E	0.066	0.243	0.088	+	+	+
32	5	0.2	D	D	D	0.103	0.479	0.024	+	+	+
33	5	0.5	E	E	E	0.045	0.324	0.145	-	+	+
34	5	0.5	E	E	D	0.058	0.238	0.431	-	+	+
35	5	0.5	E	D	E	0.043	0.198	0.295	-	+	+
36	5	0.5	E	D	D	0.039	0.309	0.143	+	+	+

37	5	0.5	D	E	E	0.043	0.340	0.128	-	+	+
38	5	0.5	D	E	D	0.045	0.435	0.177	-	+	+
39	5	0.5	D	D	E	0.063	0.132	0.580	-	+	+
40	5	0.5	D	D	D	0.053	0.369	0.061	-	+	+
41	5	0.8	E	E	E	0.072	0.104	0.221	-	+	+
42	5	0.8	E	E	D	0.079	0.285	0.189	-	+	+
43	5	0.8	E	D	E	0.065	0.227	0.158	-	+	+
44	5	0.8	E	D	D	0.065	0.262	0.163	-	+	+
45	5	0.8	D	E	E	0.065	0.130	0.220	-	+	+
46	5	0.8	D	E	D	0.095	0.145	0.273	-	+	+
47	5	0.8	D	D	E	0.101	0.098	0.266	+	+	+
48	5	0.8	D	D	D	0.096	0.312	0.103	-	-	+

VITA

Hongsuk Park completed his B.S. degree from Weapons Engineering at Korea Military Academy in 1996 and his Master's degree from TEPP (Techno-Economics Policy Program) in Seoul National University in 2005. He worked as a military officer and helicopter pilot for 15 years. Since 2005, he worked as a Defense Technology Management Officer at Project Management Groups, ROKA Headquarters. He entered the Industrial and Systems Engineering Ph.D. program in September 2006. His research interest lies in the Management of Defense Technology including Modeling and Simulation, heuristic optimization and strategic control for batch process systems. His permanent address is 241 Zachry, 3131 TAMU, College Station, TX, 77843.