Production Scheduling and System Configuration for Capacitated Flow Lines with Application in the Semiconductor Backend Process

by

Mengying Fu

A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Approved April 2011 by the
Graduate Supervisory Committee:

Ronald Askin, Co-Chair
Mohong Zhang, Co-Chair
John Fowler
Rong Pan
Arunabha Sen

ARIZONA STATE UNIVERSITY

May 2011

ABSTRACT

A good production schedule in a semiconductor back-end facility is critical for the on time delivery of customer orders. Compared to the front-end process that is dominated by re-entrant product flows, the back-end process is linear and therefore more suitable for scheduling. However, the production scheduling of the back-end process is still very difficult due to the wide product mix, large number of parallel machines, product family related setups, machine-product qualification, and weekly demand consisting of thousands of lots.

In this research, a novel mixed-integer-linear-programming (MILP) model is proposed for the batch production scheduling of a semiconductor back-end facility. In the MILP formulation, the manufacturing process is modeled as a flexible flow line with bottleneck stages, unrelated parallel machines, product family related sequence-independent setups, and product-machine qualification considerations. However, this MILP formulation is difficult to solve for real size problem instances. In a semiconductor back-end facility, production scheduling usually needs to be done every day while considering updated demand forecast for a medium term planning horizon. Due to the limitation on the solvable size of the MILP model, a deterministic scheduling system (DSS), consisting of an optimizer and a scheduler, is proposed to provide sub-optimal solutions in a short time for real size problem instances. The optimizer generates a tentative production plan. Then the scheduler sequences each lot on each individual machine according to the tentative production plan and scheduling rules. Customized factory rules and additional resource constraints are included in the DSS, such as preventive maintenance schedule, setup crew availability, and carrier limitations. Small problem instances are randomly generated to compare the performances of the MILP model and the deterministic scheduling system. Then experimental design is applied to understand the behavior of the DSS and identify the best configuration of the DSS under different demand scenarios.

Product-machine qualification decisions have long-term and significant impact on production scheduling. A robust product-machine qualification matrix is critical for meeting demand when demand quantity or mix varies. In the second part of this research, a stochastic mixed integer programming model is proposed to balance the tradeoff between current machine qualification costs and future backorder costs with uncertain demand. The L-shaped method and acceleration techniques are proposed to solve the stochastic model. Computational results are provided to compare the performance of different solution methods.

ACKNOWLEDGEMENTS

I would like to thank everyone that helped make this dissertation possible.

First, I would like to thank my committee members. I thank Dr. Ronald Askin for being a great advisor. Without his guidance, encouragement, support, and patience, I would have never finished this dissertation. I would also like to thank my co-advisor Dr. Muhong Zhang for her assistance. I am deeply grateful to her for the long discussions that helped me resolve difficult optimization problems. Thanks to Dr. John Fowler for insightful comments and suggestions at different stages of my research and study. Thanks for Dr. Rong Pan and Dr. Arunabha Sen, who graciously agreed to serve on my committee, for their very helpful insights, comments and suggestions at my proposal meeting.

Then, I would like to acknowledge faculty members in the School of Computing, Informatics, and Decision Systems Engineering at Arizona State University for numerous discussions and lectures on related topics that helped me improve my knowledge in the area.

Additionally, I appreciate the financial support from Intel that funded parts of the research discussed in this dissertation.

Finally, I would like to thank my fellow graduate students, alphabetically: Junzilan Chen, Moeed Haghnevis, Wandaliz Torres Garcia, Serhat Gul, Shrikant Jarugumilli, Jinjin Li, Qing Li, Paul Maliszewski, Adrian Ramirez Nafarrate, Shanshan Wang, Liangjie Xue, Mingjun Xia, for their friendship and support throughout this process.

Last but not least, I would like to thank my parents for supporting me to explore my own potential. All the love and understanding they have provided me over the years was the greatest gift anyone has ever given me.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Table Page

CHAPTER 1

INTRODUCTION

This research addresses the production scheduling of semiconductor back-end facilities, but the proposed methods could be applied to any process that has a similar structure. Semiconductors, also referred as integrated circuits (ICs), are contained in many commonly used electrical and electronic devices. There are numerous electrical pathways connecting to billions of transistors on the semiconductors. Those transistors perform binary operations by either holding an electric charge or holding little/no charge. Semiconductor manufacturing process consists of 9 main steps.

Step 1 Silicon is used to grow silicon crystals that are then sliced into wafers;

Step 2 One side of each wafer is polished, on which chips are built;

Step 3 A layer of silicon dioxide glass is grown on the polished side of the wafer;

Step 4 Photolithography is used to create a layer of circuit patterns on the chip;

Step 5 The wafer goes to the etch area where materials are removed in a series of steps, resulting a pattern of silicon dioxide on top of the wafer;

Step 6 Through several photolithography and etch steps, subsequent layers of various patterned materials are built up on the wafer to form the multiple layers of circuit patterns in a single chip (re-entrant product flow);

Step 7 Certain areas of the wafer are exposed to chemicals that change their ability to conduct electricity;

Step 8 A conducting metal (usually copper) is first electro-plated on the entire wafer surface and then polished off selectively, leaving thin lines of metal interconnects;

Step 9 First, each chip is tested for electrical performance and sorted accordingly; then, each chip is put into an individual package; at last, chips are tested again to make sure they function properly.

Operations in steps 1-8 are usually called the front-end process or wafer fabrication, and the assembly and test operations in step 9 are called the back-end process. A typical semiconductor assembly and test facility has approximately 30 aggregated product families, 30 nearly linear processing operations, and more than 300 machines on the floor. Orders of the same product family are grouped into lots of 1024 units. Weekly demand consists of more than a thousand lots with a throughput time as long as a couple of weeks. As the last section of semiconductor manufacturing, meeting customer orders on time is the most important criterion, in particularly we desire to minimize the total tardiness. When the demand exceeds the capacity, the priority of each lot needs to be considered. For example, confirmed customer orders have higher priorities than internal orders based on forecast, and some order is more profitable than others, thus assigned a higher priority. Therefore the objective of the production scheduling in this research is to minimize the total prioritized tardiness.

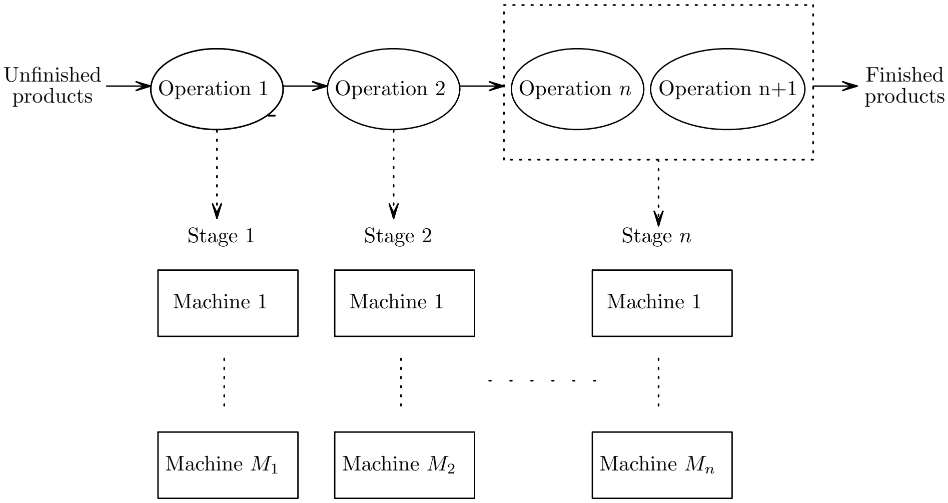


Figure 1.1: Semiconductor Back-end Process

The production system modeled in this research is shown in Figure 1.1. There is a unique route, which is a list of sequential operations, for each product family. The product flow in the back-end process is unidirectional, compared to the front-end process which is dominated by reentrant operations. However, some operations or stages could be skipped for some product families. There are unrelated parallel machines at each stage, which can perform the same operation(s). A machine can only process product families that it has been qualified for. The product-machine qualification is a production system configuration decision and represented by a two-dimensional 0-1 matrix. There could be more than one operation performed at one stage with different sequences. The processing times for the same operation and product family at different machines can be different, which are determined by the machine type. There is a sequence-dependent setup when a machine switches between product families or operations. When an operation is started on a machine, no interruption is allowed (non-preemptive scheduling). The production system described so far can be characterized as a flexible flow shop with family-related sequence-dependent setup times, product-machine qualification, and multiple operations at one stage. A novel mixed integer linear programming model is proposed in this research for the medium term (e.g. several weeks) production scheduling of the above system. It is shown in Gupta [1988] that a two-stage flexible flow shop scheduling problem with a single machine at one stage is NP-hard. Since that problem can be seen as a special case of the general flexible flow shop scheduling problem with setup considerations, it could then be concluded that the general flexible flow shop scheduling problem with setups is also NP-Hard. Moreover, there are product-machine qualifications, multiple operations at one stage, and customized constraints in the semiconductor back-end process, which are not usually considered in the classic flexible flow shop scheduling models. Customized constraints include machine preventive maintenance schedules, machine engineering time schedules, and the availability of other resources in the manufacturing process such as staff for setups, tools, etc. Those constraints are non-neligible in the scheduling process, and also make the scheduling problem even more difficult. A deterministic scheduling system is proposed to provide a sub-optimal production schedule for real size problem instances in a short time while considering all important customized constraints in the shop floor.

In a semiconductor back-end facility, each machine needs to be configured for the product families it will process in the future. The configuration process includes installing and testing a software program for each product on the machine. The configuration of the production system with respect to product families is represented by the product-machine qualification matrix, which is a two-dimensional $0-1$ matrix with 1 meaning the corresponding machine qualified for the corresponding product and 0 otherwise. Product-machine qualification decisions are critical because of their long-term impact on future production scheduling. Usually not all machines are qualified for all product families in a back-end facility. The first reason is that not all machines are technologically capable of processing all products due to the fast development of new products and machines in the semiconductor industry. The second reason is that qualifying all machines for all products is not financially efficient. On the other hand, the product-machine qualification should be robust enough to handle future demand with different quantities or mix. As a result, product-machine qualification decisions are complex because of the wide product mix, large number of machines, and demand uncertainty. In this research, a stochastic model is proposed to to minimize product-machine qualification cost while considering future production scheduling with demand uncertainty.

The remainder of the dissertation is organized as follows. Chapter 2 is a comprehensive literature review about general production scheduling, production scheduling in a semiconductor back-end facility, and product-machine qualifications. In

Chapter 3, a MILP formulation is presented and described for solving the flexible flow line scheduling problem with family-related sequence-independent setup times, product-machine qualification, and multiple operations at one stage. This is followed by Chapter 4, in which a deterministic scheduling system is proposed for the semiconductor back-end operations scheduling with the ability to consider all additional constraints and solve large problem instances in a reasonable time. In Chapter 5, computational experiments and results are presented to show solvable size of the MILP formulation, comparison between the DSS solutions and the optimal solutions for small problem instances, and the behavior of the DSS for real size problem instances. in Chapter 6, a stochastic model and several solution methods are proposed for product-machine qualification optimization in the back-end facility. Computational results are presented to show the comparison between the deterministic and stochastic models as well as different solution methods of the stochastic model. Finally, this research is concluded in Chapter 7.

CHAPTER 2

LITERATURE REVIEW

Literature related to our scheduling problem and production-machine qualification optimization is reviewed in this chapter.

2.1 Flow Shop Scheduling

First, literature on flow shop scheduling problems with setup times is discussed. A flow shop is a multi-stage production system with more than one parallel machines at each stage and all products going through the system unidirectionally, e.g. stage 1, then stage 2, and so on. The area of flow shop scheduling has been extensively studied in the past 50 years since Johnson [1954]. There are thousands of papers about different optimal procedures and heuristics for solving the flow shop scheduling problem and its variants. Quadt and Kuhn [2007] gave a comprehensive review about different solution procedures of the flow shop scheduling problem. Most optimal procedures are based on Branch & Bound and setup times are not included in modeling. Salvador [1972] proposes a Branch & Bound algorithm that generates a permutation schedule, e.g. the same sequence of jobs at every stage. Brah and Hunsucker [1991] develop another Branch & Bound algorithm based on searching the space of possible job sequences for each parallel machine stage by stage, generating a non-permutation schedule. Brockmann and Dangelmaier [1997], Brockmann et al. [1998] develop and improve a parallelized version of the algorithm presented by Brah and Hunsucker [1991], speeding up the computation by using multiple computer processors. Portmann et al. [1998] improve Brah and Hunsucker [1991] by using a genetic algorithm to derive upper bounds during the Branch & Bound procedure. Carlier and Néron [2000] consider all the stages simultaneously and generate search tree by selecting sequentially a stage and the next job to be scheduled at that stage. Néron et al. [2001] implement the concepts of 'energetic reasoning' and 'global operation' to speed up the procedure. Harjunkoski and Grossmann [2002] propose a algorithm that iteratively assign jobs to machines and then sequence the jobs assigned to one machine. More detail about exact optimal solution procedures for flow shop scheduling problems can be found in Kis and Pesch [2005].

However, flow shop scheduling models with exact solution procedures are usually simplified compared to the real processes, and thus difficult to be applied in a real facility. The exact solution procedures also take a fairly long time and therefore could only handle small size problems within a reasonable time. As a result, heuristics are developed to provide faster solutions (usually not optimal) or deal with real size problem instances. Agnetis et al. [1997] propose a simple heuristic to select next job from the queue using dispatching rules whenever a machine becomes idle. Some heuristics use local search methods or metaheuristics. The difference between the two is that local search methods accept a new solution only if it is better than current solution while metaheuristics also accept worse solutions to avoid local optimum. Comparisons of several tabu search heuristics by Hurink et al. [1994], Dauzère-Pérès and Paulli [1997], and Nowicki and Smutnicki [1998] can be found in Negenman [2001]. Leon and Ramamoorthy [1997] propose a different way of applying local search in flow shop scheduling, searching neighborhood of the input data rather than the neighborhood of the schedule. The above heuristics solve the flowshop scheduling problem in a integrated way. Another large category of heuristics decompose the problem based on stage or job. Stage-oriented decomposition approaches divide the whole problem into several single stage, multiple machine scheduling subproblems. Mokotoff [2001] gives an review of single stage multiple machine scheduling problem. Most stage-oriented decomposition approaches are based on 'list schedules', introduced by Graham [1969] for single stage multiple machine scheduling problem. List schedules can be adapted with standard flow line algorithm or with local search or metaheuristics, for the coordination between stages. In the first method, jobs are sequenced by the aggregated standard flow line (a flow line with single machine at each stage) algorithm (see Cheng et al. [2000] for an overview) for a selected stage. Then parallel machines at that stage are considered explicitly and a machine is selected for each job using list schedules. The next stage is scheduled similarly using the job sequence from the previous stage. See Ding and Kittichartphayak [1994], Lee and Vairaktarakis [1994], Guinet and Solomon [1996], Botta-Genoulaz [2000], Koulamas and Kyparisis [2000], and Soewandi and Elmaghraby [2001] for more variants of this method. In the latter method, local search or metaheuristics are used to create and improve initial job sequence [Kochhar and Morris, 1987, Jin et al., 2002, Kurz and Askin, 2004]. Job-oriented decomposition approaches schedule all jobs sequentially with one job each time at all stages [Sawik, 1993, Gupta et al., 2002, Phadnis et al., 2003].

2.2 Flexible Flow Shop Scheduling

If a flow shop is “flexible”, some products can skip some stages. Usually in a flow shop, all the parallel machines at the same stage are identical and can only perform one operation. However, in a semiconductor back-end facility and also in some other factories (with very different product families), parallel machines could belong to different machine types. Each machine type may only process a subset of product families and has its unique processing time for each product family. In this case, the parallel machines are called unrelated. The machines used to test packaged chips can perform different types of tests, and there is a minor setup time between different tests even for the same lot. Those above two characteristics, product-machine qualification and multiple operations at one stage, are usually not considered in the classic flexible flow shop scheduling literature. The flexible flow shop structure is very commonly used in manufacturing industry and thus has drawn considerable attention in scheduling research. Flexible flow shop scheduling problems with setup times can be divided into four categories depending on what types of setup time is considered: sequence-independent or sequence-dependent setup times, and non-batch (job based) or batch (product family based) setup times. Sequence-dependent or batch setup times makes the scheduling problem much more difficult compared to its counterpart. Due to the complexity of the problem, most literature on flexible flow shop with setup times focuses on developing heuristics. The flexible flow shop scheduling problem with non-batch sequence-dependent setup times is first formulated by Liu and Chang [2000] as a separable integer programming problem and provides a search heuristic based on Lagrangian relaxation. The scheduling objective is minimizing earliness, tardiness, and setup cost. The scheduling time horizon is also divided into time periods, and all setup/processing times are measured in units of time periods. Four heuristics for flexible flow shop scheduling with non-batch sequence-dependent setup times are reviewed by Kurz and Askin [2004], based on lower bounds developed in the paper. A two-stage flexible flow shop with a single machine at the first stage and parallel uniform machines at the second stage is modeled by Huang and Li [1998] while considering batch sequence-independent setup times. Two lower bounds and two heuristics based on sequencing rules are proposed and tested with problems up to 5 product families, 15 lots in each product family, and 8 machines at stage 2. The objective is to minimize the makespan and the heuristic solutions are 20% to 60% above the lower bounds. A general flexible flow shop with batch sequence-independent setup with grouped jobs is studied by Logendran et al. [2005] with the objective of minimizing the makespan and a two-level group scheduling strategy is implemented: first sequencing within the group and then sequencing the groups.

Three different heuristic algorithms are compared using statistical experiments, in which problems up to 7 stages, 7 product families, and 10 lots in each product family are solved. Group technology is also considered by both Andres et al. [2005] and Logendran et al. [2006]. A case study from a label sticker manufacturing company is provided by Lin and Liao [2003]. The manufacturing process consists of two stages: a high speed machine requiring batch sequence-dependent setups at the first stage, and two different types of dedicated machines with negligible setups at the second stage. The scheduling objective is to minimize the weighted maximal tardiness. Scheduling rules based on sequencing and dispatching methods are proposed and tested on small sized problems. Recently, metaheuristic algorithms have been used to generate schedules for complex manufacturing systems. Ruiz and Maroto [2006] propose a generic algorithm to solve a general flexible flow shop scheduling with non-batch sequence-dependent setup times and machine eligibility. The algorithm is compared to adaptations of other metaheuristics with problems up to 200 jobs and 20 stages. For a comprehensive up-to-date review on scheduling problems with setup considerations, the reader is referred to Allahverdi et al. [2008]. The product-machine qualification and setup considerations make the problem more difficult compared to general flexible flow line scheduling problems.

2.3 Semiconductor Back-End Process Scheduling

In addition to the literature studying general flexible flow shop scheduling problems with batch setup times, research has also been done specifically for scheduling in semiconductor back-end facilities. A disjunctive graph is used to model the workcenters in a test facility in Uzsoy et al. [1991]. Computational results are provided for up to 5 lots with 15 operations. Since each lot is modeled explicitly in this model, the problem size increases when the number of lots to be scheduled becomes larger. This limits the implementation of the method in real time scheduling because a semiconductor test facility usually processes thousands of lots each week. A simulation based scheduling and optimization framework is first proposed for the semiconductor back-end process in Sivakumar [1999]. An offline deterministic simulation model is built and customized to implement scheduling rules that try to improve cycle time, delivery, and utilization, while considering related resource constraints and down stream work-in-process(WIP) status. In Sivakumar and Chong [2001], a data driven discrete event simulation model is used to study the impact of different control parameters in the current production scheduling strategy on the cycle time distribution and throughput of a semiconductor back-end facility. In Liu et al. [2005], a lot release strategy is developed for the semiconductor back end facility, based on lot prioritization and capacity constraints, along with other control mechanism such as machine loading strategy to minimize conversions. In a more recent study Werner et al. [2006], an online simulation model for a semiconductor back-end facility is built, and then the lot release strategy as well as the lot sequence on the bottleneck stages are improved using Threshold Accepting. Later in Weigert et al. [2009], the same system is optimized using iterative heuristic search strategies under multiple objectives. In Chiang et al. [2008], fuzzy analytical hierarchy process (AHP) is introduced to the scheduling process to identify a acceptable WIP deviation level at each bottleneck operation, which is then used to set lot priority in the scheduling process. The method is tested in a simulation model with real-world data. Customer satisfactory and on-time delivery are the main objective in this paper. In Jarugumilli et al. [2008], an optimization-simulation framework and a mixed-integer-linear-programming formulation are proposed for weekly execution level capacity allocation in an assembly-test facility. The scheduling horizon is divided into 2-hr time buckets and sequence-independent batch setup times (assumed to be no longer than 4 hrs) are considered in the mixed integer linear programming (MILP) formulation. An improved MILP formulation compared to Jarugumilli et al. [2008] will be given in this paper, by assuring that lots will be released to the next stage every 2 hours only when they are completed at the current stage and removing the restriction on the setup time length.

2.4 Product-Machine Qualifications

Product-machine or operation-machine qualification is a very common feature in the modern semiconductor manufacturing process. A few papers consider this feature in their scheduling models [Hurink et al., 1994, Jurisch, 1995, Brucker et al., 1997, Mati and Xie, 2004, Wu et al., 2006, 2008], but none of them proposes to change or optimize the current machine qualification. There are also some other papers that utilize short-term machine dedication to schedule the production activities [Campbell, 1992, Bourland and Carl, 1994]. An operation-machine qualification management system is proposed by Johnzén et al. [2008] for a semiconductor front-end facility, in which four flexibility measures are developed to evaluate different operation-machine qualifications. Impact of different operation-machine qualifications, with different scores according to the four flexibility measures, on production scheduling is showed through simulation. Aubry et al. [2008] present a mixed integer linear programming model (MILP) for the product-machine qualification optimization of parallel multi-purpose machines. The objective is to minimize machine configuration costs while obtaining a load-balanced capacity allocation. The MILP formulation is proved to be strongly NP-hard but could be relaxed to a transportation problem under certain assumptions. Rossi [2010] presents a robustness measure for the multi-purpose machine configuration model developed by Aubry et al. [2008]. Maximal disturbance of the demand that changes the optimal configuration is used as the robustness measure. Ignizio [2009] proposes a binary optimization model for the operation-machine qualification of photolithography machines in a wafer fabrication factory. The objective is to obtain a load-balanced schedule at minimal machine qualification costs. The cycle time in the factory is shown to be decreased using the binary optimization model compared to machine qualifications developed by heuristic or “educated guess” means. In somewhat related work, Drexl and Mundschenk [2008] propose an integer programming model for long-term employee staffing based on qualification profiles. The objective is to accomplish all tasks with minimal total employment costs. Employee scheduling could be another application area of the methodologies developed for the machine qualification management in the factory.

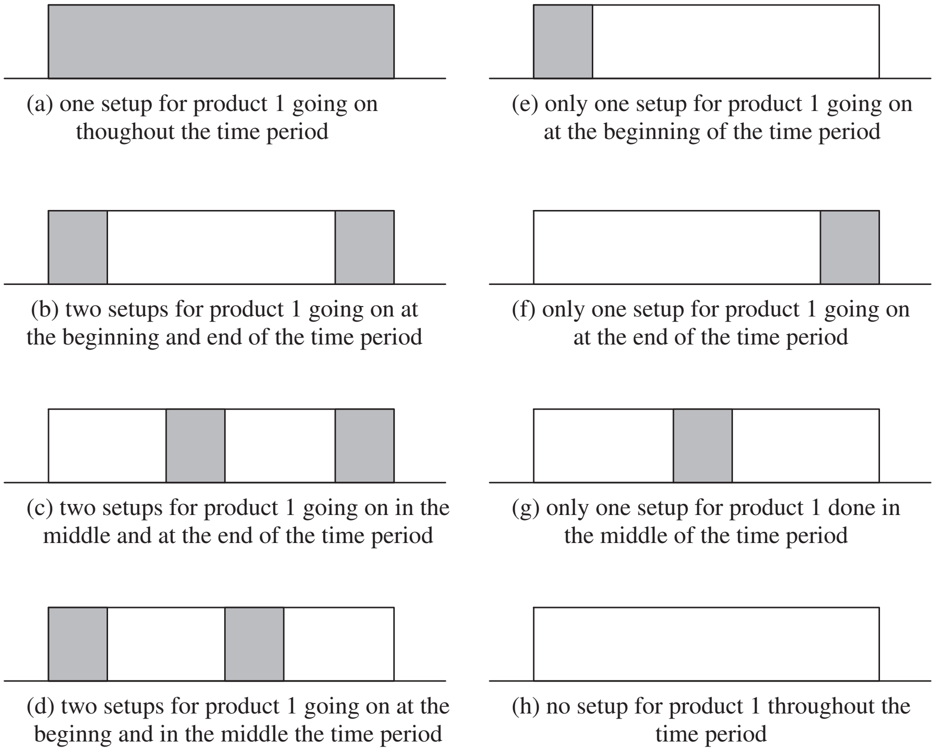
CHAPTER 3

OPTIMIZATION MODEL

The semiconductor back-end process is a flexible flow shop with product family related sequence-independent setup times. There are N stages in the system, with $M[n]$ parallel machines at stage n. Weekly demand forecasts for P products are given in lots for a few weeks. Backorder is allowed, and backorder cost is cumulated in every day/time period to minimize the total tardiness. Production and material handling in the system are both processed in lots. When a machine finishes processing a lot and starts to process another lot of a different product, a setup needs to be done first and the setup time only depends on the new product (sequence-independent). Once a machine starts processing a lot, it is occupied until the lot is finished (non-preemptive). The scheduling horizon is divided into small time buckets, and finished lots in one time bucket will only be available for the next stage in the next time bucket. A natural way of determining the time buckets is by the frequency of the material handling system. The length of the time buckets has to be chosen carefully. If it is too long, there would be a large time lag (delay) in the schedule generated. If it is too short, there would be a huge number of time related decision variables in the formulation, which will slow down the solution of the formulation.

The following Figure 3.1 shows all possible scenarios for the setup of product 1 as an example during one time period. Dark grey parts in the figure are the setup for product 1, and white parts are either production of the product or setup/production of other products. Figure 3.1 (a) is the scenario in which the setup for product 1 starts before the beginning of time period and is still going on at the end of the time period. Figure 3.1 (b) is the scenario in which one setup for product 1 starts before the beginning of the time period and ends during the time period followed by another setup for product 1 starting during the time period and still going on at the end of the time period. Figure 3.1 (c) is the scenario in which one setup for product 1 starts and ends during the time period followed by another setup for product 1 starting during the time period and still going on at the end of the time period. Figure 3.1 (d) is a possible scenario, but it can not happen in the optimal solution. Because if two setups for the same product ends during one time period, the production after the second setup can always be combined with the production after the first setup and the time for the second setup would be saved without changing any other part of the solution. So in our MIP formulation, scenario in Figure 3.1 (d) is not considered. Figure 3.1 (e) is the scenario in which there is only one setup for product 1, starting before the time period and ending during it. Figure 3.1 (f) is the scenario in which there is only one setup for product 1, starting during the time period and still going on at the end of it. Figure 3.1 (g) is the scenario in which there is only one setup for product 1, starting and ending during the time period. Figure 3.1 (h) is the scenario in which there is no setup for product 1 throughout the time period. The setup carryover and continuation constraints in the following MILP formulation considers all the scenarios in Figure 3.1 except (d).

The following MILP formulation is based on the MILP formulation first proposed inJarugumilli et al. [2008]. But the following new MILP formulation makes sure that fractional lots would not be available for the next stage until they are completely finished. Also the setup continuation variables and constraints allow setup time to cross more than two time periods. We assume only one operation is performed at each stage. All products go through all stages sequentially, and all machines are qualified to process every product. The formulation could be easily generalized through subscripts to include more than one operation at each stage, different operation routes for different products, transportation/material-handling time



(a) one setup for product 1 going on thoughout the time period

(b) two setups for product 1 going on at the beginning and end of the time period

(c) two setups for product 1 going on in the middle and at the end of the time period

(d) two setups for product 1 going on at the beginng and in the middle the time period

(e) only one setup for product 1 going on at the beginning of the time period

(f) only one setup for product 1 going on at the end of the time period

(g) only one setup for product 1 done in the middle of the time period

(h) no setup for product 1 throughout the time period

Figure 3.1: Setup Scenarios During One Time Period

between operations, product-machine qualification, and product substitution (substitute lower-speed chips with faster-speed chips) in the semiconductor back-end process. We have already implemented the generalized model with all those extensions, which is shown in Appendix A. In the generalized formulation, if bottleneck stages are identified, only the bottleneck stages will be included in the model first so that the problem size can be decreased. Estimated throughput times of those non-bottleneck stages from historical data are used to model delays between bottleneck stages.

Notation:

P: number of products, with index p

N: number of stages, with index n

$M[n]$: number of parallel machines at stage n

T: number of time periods, with index t

K: a big number

C: capacity of one machine per time period, which can also be machine and/or time period dependant denoted by $C_{n,m,t}$

$B_{p,0}$: initial back order quantity (in lots) of product p

$I_{p,n,0}$: initial integral inventory (in lots) of product p after stage n

$\tilde{X}_{p,n,m,0}$: initial fractional production quantity (in lots) of product p on machine m at stage n

b_p: back order cost of product p per lot per time period

$d_{p,t}$: demand quantity (in lots) of product p at the end of time period t

$s_{p,n,m}$: set up time for product p on machine m at stage n

$t_{p,n,m}$: lot processing time of product p on machine m at stage n

Continuous Decision Variables:

$X_{p,n,m,t}$: production quantity (in lots) for product p on machine m at stage n in time period t

$\tilde{X}_{p,n,m,t}$: fractional(unfinished) production quantity (in lots) for product p on machine m at stage n at the end of time period t

$W^1_{p,n,m,t}$: time for the setup that ends in time period t for product p on machine m at stage n in time period t

$W^2_{p,n,m,t}$: time for the setup time that continues in time period $t+1$ for product p on machine m at stage n in time period t

$L_{p,n,m,t}$: cumulative setup time for an unfinished setup in process at the end of time period for product p on machine m at stage n

Integer Decision Variables:

$\bar{X}_{p,n,m,t}$: integral production quantity (in lots) for product p finished on machine m at stage n in time period t

$\lceil \tilde{X} \rceil_{p,n,m,t}$: smallest integer that is equal to or larger than $\tilde{X}_{p,\ n,\ m,\ t}$

$I_{p,n,t}$: integral inventory quantity (in lots) of product p at the end of time period t after stage n

$B_{p,t}$: integral back order quantity (in lots) of the product p at the end of time period t

Binary Decision Variables:

$Y_{p,n,m,t}$: 1 if a setup for product p on machine m at stage n ends in period t; 0 otherwise

$Z_{p,n,m,t}$: 1 if product p can be processed on machine m at stage n in time period $t+1$ without a setup; 0 otherwise

$U_{p,n,m,t}$: 1 if a setup for product p is going on at the end of the period t and will continue at the beginning of period $t+1$ on machine m at stage n; 0 otherwise

[BPSS]

$$min \quad \sum_{p,t} b_p B_{p,t} \tag{3.1}$$

$$s.t. \quad I_{p,n,t-1} + \sum_m \bar{X}_{p,n,m,t} - \sum_m \bar{X}_{p,n+1,m,t} - \sum_m \lceil \tilde{X} \rceil_{p,n+1,m,t} + \sum_m \lceil \tilde{X} \rceil_{p,n+1,m,t-1}$$

$$= I_{p,n,t}, \; \forall \; p, n < N, t \tag{3.2}$$

$$\sum_m \bar{X}_{p,n,m,t} + \sum_m \lceil \tilde{X} \rceil_{p,n,m,t} - \sum_m \lceil \tilde{X} \rceil_{p,n,m,t-1} \leq I_{p,n-1,t-1}, \; \forall p, n \geq 2, t \tag{3.3}$$

$$I_{p,N_p,t-1} - B_{p,t-1} + \sum_m \bar{X}_{p,N_p,m,t} - d_{p,t} = I_{p,N_p,t} - B_{p,t}, \; \forall p, t \tag{3.4}$$

$$\tilde{X}_{p,n,m,t-1} + X_{p,n,m,t} = \tilde{X}_{p,n,m,t} + \bar{X}_{p,n,m,t}, \; \forall p, n, m, t \tag{3.5}$$

$$\lceil \tilde{X} \rceil_{p,n,m,t} - 1 < \tilde{X}_{p,n,m,t} \leq \lceil \tilde{X} \rceil_{p,n,m,t}, \; \forall p, n, m, t \tag{3.6}$$

$$\sum_p t_{p,n,m} X_{p,n,m,t} + \sum_p (W^1_{p,n,m,t} + W^2_{p,n,m,t}) \leq C, \; \forall n, 1 \leq m \leq M[n], t \tag{3.7}$$

$$X_{p,n,m,t} \leq K(Z_{p,n,m,t-1} + Y_{p,n,m,t}), \; \forall p, n, m, t \tag{3.8}$$

$$W^1_{p,n,m,t} \leq C Y_{p,n,m,t}, \; \forall p, n, m, t \tag{3.9}$$

$$W^2_{p,n,m,t} \leq CU_{p,n,m,t}, \ \forall p,n,m,t \tag{3.10}$$

$$\sum_p Z_{p,n,m,t} + \sum_p U_{p,n,m,t} = 1, \ \forall n, 1 \leq m \leq M[n], t \tag{3.11}$$

$$Z_{p,n,m,t} \leq 1 + Y_{p,n,m,t} - Y_{q,n,m,t}, \ \forall p \neq q, n, m, t \tag{3.12}$$

$$Z_{p,n,m,t} \leq Y_{p,n,m,t} + Z_{p,n,m,t-1}, \ \forall p,n,m,t \tag{3.13}$$

$$s_{p,n,m} Y_{p,n,m,t} \leq L_{p,n,m,t-1} + W^1_{p,n,m,t}, \ \forall p,n,m,t \tag{3.14}$$

$$L_{p,n,m,t} \leq s_{p,n,m} U_{p,n,m,t}, \ \forall p,n,m,t \tag{3.15}$$

$$L_{p,n,m,t} - W^2_{p,n,m,t} \leq L_{p,n,m,t-1}, \ \forall p,n,m,t \tag{3.16}$$

$$L_{p,n,m,t} - W^2_{p,n,m,t} \leq s_{p,n,m} * (1 - Y_{q,n,m,t}), \ \forall p,q,n,m,t \tag{3.17}$$

$$\tilde{X}_{p,n,m,t} \leq Z_{p,n,m,t}, \ \forall p,n,m,t \tag{3.18}$$

$$0 \leq \tilde{X}_{p,n,m,t} < 1, \ \forall p,n,m,t \tag{3.19}$$

$$X_{p,n,m,t}, \tilde{X}_{p,n,m,t}, W^1_{p,n,m,t}, W^2_{p,n,m,t}, L_{p,n,m,t} \in \mathbb{R}^+, \ \forall p,n,m,t \tag{3.20}$$

$$\bar{X}_{p,n,m,t}, \lceil \tilde{X} \rceil_{p,n,m,t}, I_{p,n,t}, B_{p,t} \in \mathbb{Z}^+, \forall p,n,m,t \tag{3.21}$$

$$Y_{p,n,m,t}, Z_{p,n,m,t}, U_{p,n,m,t} \in \mathbb{B}, \forall p,n,m,t \tag{3.22}$$

The objective in (3.1) is to minimize the total cumulative prioritized backorder cost. Constraints (3.2) are the inventory balance constraints for each product at each stage except the last in each time period. They indicate that the inventory quantity at the end of current time period must equal to the previous inventory plus production minus consumption at next operation. $\sum_m \bar{X}_{p,n+1,m,t}$ is the total number of lots finished at stage $n+1$ in period t, $\sum_m \lceil \tilde{X} \rceil_{p,n+1,m,t}$ is the number of unfinished lots on the machines at stage $n+1$ at the beginning of period t, and $\sum_m \lceil \tilde{X} \rceil_{p,n+1,m,t-1}$ is the number of lots still in process at stage $n+1$ at the end of period t. $\sum_m \bar{X}_{p,n+1,m,t} - \sum_m \lceil \tilde{X} \rceil_{p,n+1,m,t} + \sum_m \lceil \tilde{X} \rceil_{p,n+1,m,t-1}$ is the number of lots taken from the inventory $I_{p,n,t-1}$ at stage $n+1$ in time period t , as shown in Figure 3.2. Constraints (3.3) are the material availability constraints, which state that the

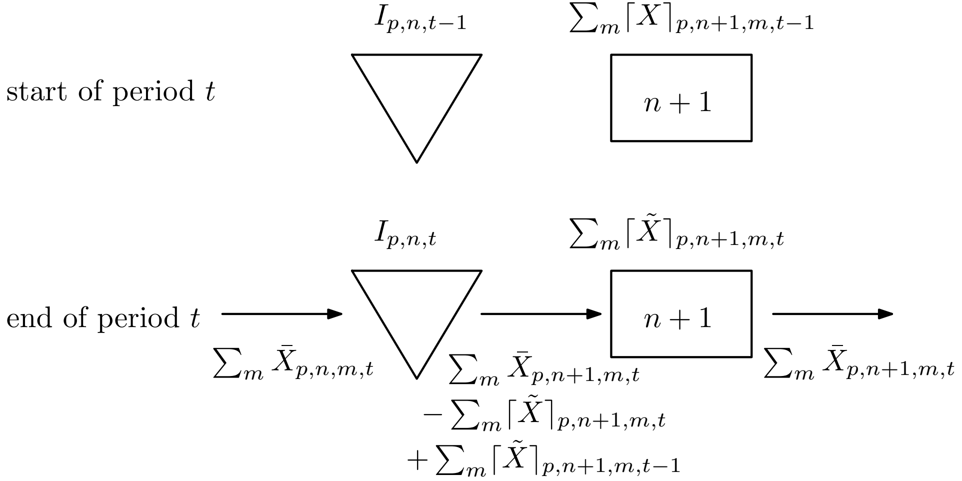

$I_{p,n,t-1}$
$\sum_m \lceil \tilde{X} \rceil_{p,n+1,m,t-1}$
start of period t
$n+1$
$I_{p,n,t}$
$\sum_m \lceil \tilde{X} \rceil_{p,n+1,m,t}$
end of period t
$n+1$
$\sum_m \bar{X}_{p,n,m,t}$
$\sum_m \bar{X}_{p,n+1,m,t}$
$-\sum_m \lceil \tilde{X} \rceil_{p,n+1,m,t}$
$+\sum_m \lceil \tilde{X} \rceil_{p,n+1,m,t-1}$
$\sum_m \bar{X}_{p,n+1,m,t}$

Figure 3.2: Inventory Update

production quantity at stage n in period t has to be less than the inventory quantity after stage $n-1$ at the end of period $t-1$. An alternative set of material availability constraints are (3.23), which allow the production quantity at stage n in period t to be available to the next stage $n+1$ in the same time period based on (3.2), but limit the maximal number of stages (λ) a lot can go through during one time period.

$$\sum_m \bar{X}_{p,n,m,t} + \sum_m \lceil \tilde{X} \rceil_{p,n,m,t} - \sum_m \lceil \tilde{X} \rceil_{p,n,m,t-1} \leq I_{p,n-1,t-1} + ... + I_{p,n-\lambda,t-1}, \quad \forall p, n \geq \lambda, t \tag{3.23}$$

Constraints (3.4) are the inventory balance constraints for each product at the last stage in each time period. Consumption at the next stage is replaced by demand. Backorders are allowed but incur cumulative backorder cost as shown in the objective expression (3.1). Constraints (3.5) update the unfinished lot for each product on each machine at the end of each time period. Constraints (3.6) define $\lceil \tilde{X} \rceil_{p,n,m,t}$'s. Constraints (3.7) are the capacity constraints for each machine in each time period. The production and setup time over all products on the machine can not exceed the capacity of the machine in the time period. Constraints (3.8) are the production constraints for each product in each time period. There will not be production unless a setup is carried over from last time period or finished in current time period. Setup carryover is modeled by decision variables $Z_{p,n,m,t}$'s. $Z_{p,n,m,t} = 1$ means that a setup for product p is carried over from time period t to $t+1$ so that at the beginning of time period $t+1$ product p can be processed on machine m at stage n without a setup. Constraints (3.9) constraint setup continuation decision variables $W^1_{p,n,m,t}$'s, saying that there is a positive setup time ending in this time period only when a setup is finished in that time period. Constraints (3.10) define setup continuation decision variables $W^2_{p,n,m,t}$'s. There is a positive setup time continuing in the next time period only when the setup is not finished at the end of the time period. Constraints (3.11) indicate that at the end of any time period, a machine is either being setup or producing for a product. Constraints (3.12) indicate that if there is a setup finished for product q in the time period, the setup status for product p can be carried over to the next time period only when there is also a setup finished for product p. Constraints (3.13) indicate that the setup status can be carried over to the next time period only when there is a setup finished in the time period or a setup carryover from last time period. Constraints (3.14) link $L^1_{p,n,m,t}$ with $L^2_{p,n,m,t-1}$ through

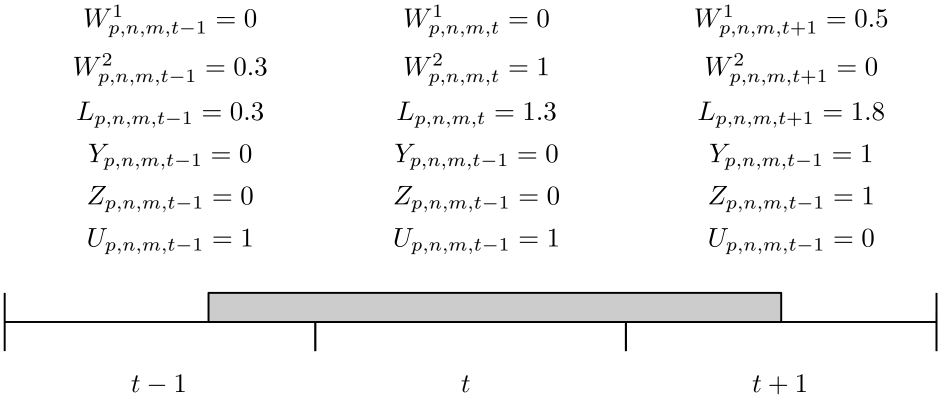


Figure 3.3: Setup Continuation

$W^1_{p,n,m,t}$. Constraints (3.15) say that $L^2_{p,n,m,t}$'s can be positive only when there is a setup continuing at the end of the time period based on the definition. Constraints

(3.16) indicate the potential link between $L^2_{p,n,m,t}$ and $W^2_{p,n,m,t} + L^2_{p,n,m,t-1}$ and constraints (3.17) limit $L^2_{p,n,m,t}$ to $W^2_{p,n,m,t}$ when there is a setup finished in time period t. The relations among $W^1_{p,n,m,t}$, $W^2_{p,n,m,t}$, and $L_{p,n,m,t}$ as well as how they are updated across time periods are shown in Figure 3.3 with a simple example. The example shows a setup for product p on machine m at stage n across three time periods $t-1$, t, and $t+1$. The setup starts at $t-1+0.7$, ends at $t+1+0.5$, and lasts for 1.8 time periods. The values of $W^1_{p,n,m}$, $W^2_{p,n,m}$, and $L_{p,n,m}$ are shown in Figure 3.3 for each time period. In real semiconductor manufacturing, setup can span several time periods but not shifts (1 shift = 12 hrs), which can be included in the model by adding an additional set of constraints forcing $U_{p,n,m,t}$'s during end-of-shift periods to be zero. Constraints (3.18) make sure the scheduling process is non-preemptive. All the remaining constraints (3.19), (3.20), (3.21), (3.22) are boundary, integral, and binary constraints.

The above MILP formulation is an innovative way of modeling the flexible flow shop scheduling problem. The optimal solution or a good upper bound of the above MILP model is very important to the flexible flow shop scheduling research because it can be used to evaluate the optimality of heuristic solutions. However, the size and solution difficulty of the above MILP formulation increase quickly when the problem size increases such as the number of products, number of machines, demand, etc. Take a real semiconductor back-end facility for example, there are about 25 products, 3 stages with $10, 1, 36$ machines, and 168 2-hr time periods (for 2 weeks). This gives us $25 \times (10+1+36) \times 168 = 197,400$ of $X_{p,n,m,t}$'s, $\tilde{X}_{p,n,m,t}$'s, $\bar{X}_{p,n,m,t}$'s, $\lceil \tilde{X} \rceil_{p,n,m,t}$'s, $W^1_{p,n,m,t}$'s, $W^2_{p,n,m,t}$'s, $L_{p,n,m,t}$'s, $Y_{p,n,m,t}$'s, $Z_{p,n,m,t}$'s, $U_{p,n,m,t}$'s each, which are $197,400 \times 5 = 987,000$ continuous variables, $197,400 \times 2 = 394,800$ integer variables, $197,400 \times 3 = 592,200$ binary variables. There are $25 \times 3 \times 168 + 25 \times 168 = 16,800$ more integer variables for $I_{p,n,t}$'s, and $B_{p,t}$'s. Constraints (3.2) to (3.19) generates more than 11 million constraints. A C++ code using ILOG CPLEX11.2 concert technology is developed in a PC with *windown XP* operating system and 2*GB* memory. The program runs out of memory before generating the complete formulation for the above real facility example. Since the problem is NP-hard, it could take a long time to solve some small size problems, as shown in Section 5.1. As a result, for the daily scheduling in a real factory, A deterministic scheduling system is presented in the following section, which not only contains all additional important constraints in the factory but also runs in reasonable time for online scheduling.

CHAPTER 4

DETERMINISTIC SCHEDULING SYSTEM (DSS)

The MILP formulation in Section 3 is very difficult to solve and thus can not be implemented in the factory for daily production planning and scheduling purpose. Besides, there are additional rules in the factory, e.g. preventive maintenance schedule, sequence dependant setup, staff availability for setting up machines. In the DSS, the following additional rules will be included:

- sequence dependent setup time: setup time depends on the previous product and current product based on the similarity between them as well as the operation being performed

- machine qualification/dedication: each machine will only be qualified to process certain products

- machine preventive maintenance (PM) schedule: preventive maintenance for each machine has to be done before the scheduled deadline

- machine engineering time (ET) schedule: engineering time schedule for each machine have to be done during the exact scheduled time period

- resource availability related to setup or production activities: including staff availability and tool set availability

- carrier capacities that limit the work-in-process inventories between certain stages

It is difficult to model all those additional details and rules in a mathematical scheduling model. To obtain a fairly good production schedule while still considering all the important rules in the factory, the DSS is proposed consisting of a optimizing module followed by a scheduling module (Figure 4.1). The optimizing module, which is called optimizer, generates an optimal production plan from a linear-programming (LP) formulation relaxed from the MILP formulation with the production quantity at each stage for each product in each time period. Neither setups nor individual machines are modeled explicitly in the LP formulation. Instead, they are modeled indirectly by decreasing machine capacity by a certain percentage or counting number of qualified machines at a certain stage. Two different optimizers are used in the DSS: one is the LP relaxation, thus called the LP optimizer, and the other is based on a backward capacity allocation logic similar to a Material-Requirements-Planning (MRP) system, thus called the MRP optimizer.

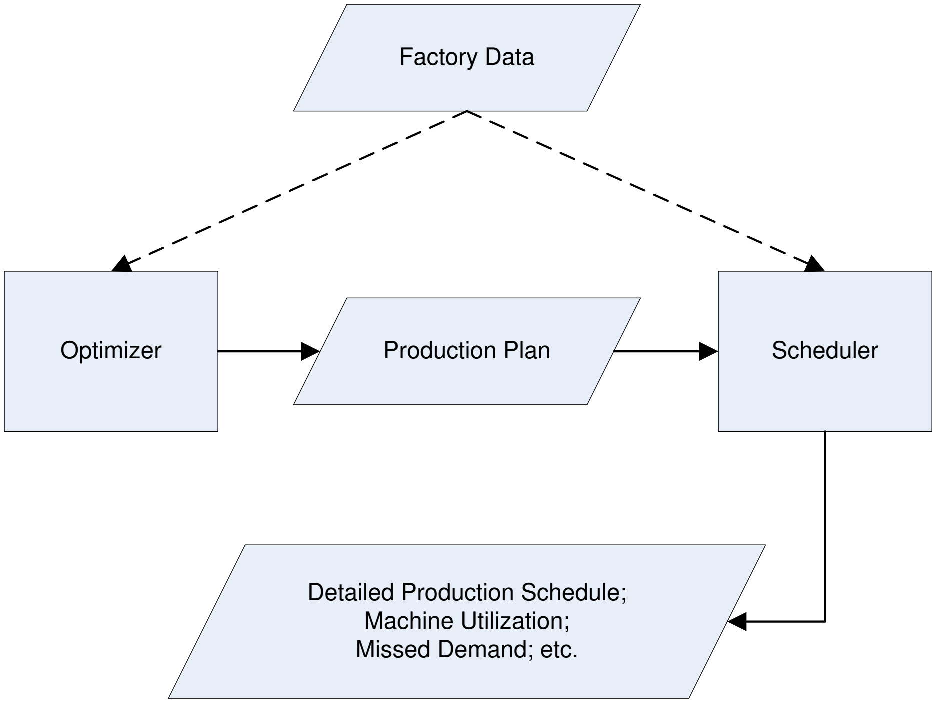


Figure 4.1: Deterministic Scheduling System (DSS)

The scheduling module, which is called the scheduler, has a deterministic discrete event system structure, and records events (setups, productions, PM's, and ET's), statistics (queue length in front of each stage, machine utilization, throughput time of each lot, etc.), status of resources (machines, staff), and material transfer (lots moving from one stage to the next) in the factory. There are two important scheduling rules in the scheduler, the dynamic lot prioritization (DLP) rule and the dynamic machine prioritization (DMP) rule. The DLP rule is used to prioritize lots in the queue when a machine becomes available, based on the product priority, setup time needed, status of other machines in the same stage, staff availability, machine qualification, PM/ET schedules, and the production plan from the optimizer. The DMP rule is used to choose a machine from a stage for a newly arrived lot, based on similar information applied in the DLP rule. Both rules are dynamic, as time changes the lot and machine priorities change too. Additional scheduling rules are also developed to improve the production schedule for multiple secondary objectives, e.g. concurrent setup limits to limit the number of setups, work-in-process (WIP) inventory limits to control the cycle time, and lot release control to avoid over production.

4.1 Optimizer

Two optimizers are developed to provide a production plan with a production quantity for each product at each stage during each time period as an input to the scheduler. The MRP optimizer takes each demand quantity with the due date and calculates the latest production start time (*LPST*) backward at each stage by counting back the lead-time, as shown in Equation (4.1) and Equation (4.2).

$$LPST_{p,t,N_p} = t - max\{\frac{D_{p,t} \times t_{p,N_p}}{M_P[N_p]}, t_{p,N_p}\}, \text{for stage } N_p \quad (4.1)$$

$$LPST_{p,t,n} = LPST_{p,t,n+1} - \max\{\frac{D_{p,t} \times t_{p,n}}{M_p[n]}, t_{p,n}\}, \text{for stage } n = N_p - 1 \text{ to } 1 \quad (4.2)$$

where,

$D_{p,t}$ = demand quantity for product p in time period t,

$LPST_{p,t,n}$ = latest production start time at stage n for the $D_{p,t}$ lots for product p in time period t,

$t_{p,n}$ = lot processing time for product p at stage n,

$M_p[n]$ = number of machines qualified for product p at stage n.

For each demand quantity $D_{p,t}$ for product p with the due date t, the calculation process starts at the last stage N_p. In order to satisfy the demand quantity $D_{p,t}$ at the end of time period t, the production should be started at stage N_p no later than time period $LPST_{p,t,N_p}$ given by Equation (4.1), since it would take at least the amount of time given by $max\{\frac{D_{p,t} * t_{p,N_p}}{M_P[N_p]}, t_{p,p}\}$ to finish the production at stage N_p. Then Equation (4.2) calculates the latest production start time period $LPST_{p,t,n}$ from stage $N_p - 1$ to stage 1 sequentially.

An alternative method to the above MRP optimizer is not to assign the same $LPST$ for all the $D_{p,t}$ lots for product p in time period t. Instead, the $D_{p,t}$ lots will be allocated evenly in the $max\{\frac{D_{p,t} \times t_{p,n}}{M_P[n]}, t_{p,n}\}$ time periods at stage n, each of which will be assigned as the $LPST$ for all the lots allocated in it. Thus in this plan, the $LPST$'s of some lots are larger than those in the MRP plan. However, the following linear programming formulation could generate a better plan than the alternative method within a reasonable time, so this alternative method is not included in the computational experiment.

From the MRP optimizer, all the lots of the same product with the same due date have the same $LPST$'s at each stage. Machine capacity shared between different products is not considered. All qualified machines are assumed to be fully available. The following LP optimizer will generate a more accurate $LSPT$ for each lot while considering machine capacity interaction between products. The mathematical formulation for the LP optimizer is shown below. It is a simplified linear relaxation of the MILP formulation in Section 3. This LP formulation does not consider setup or individual machines. But it does consider qualification relations between products and machines indirectly through available capacity for products at each stage, as shown in Equation (4.8). And setup time can also be modeled indirectly through decreasing the machine capacity in Equation (4.7) by a certain percentage.

$$min \quad \sum_{p,t} b_p B_{p,t} \tag{4.3}$$

$$s.t. \quad I_{p,n,t-1} + X_{p,n,t} - X_{p,n+1,t} = I_{p,o,t}, \ \forall \ p, n < N_p, t \tag{4.4}$$

$$X_{p,n,t} \leq I_{p,n-1,t-1}, \ \forall p, n \geq 2, t \tag{4.5}$$

$$I_{p,N_p,t-1} - B_{p,t-1} + X_{p,N_p,\ t} - d_{p,t} = I_{p,N_p,t} - B_{p,t}, \ \forall \ p, t \tag{4.6}$$

$$\sum_{p,m} t_{p,n} X_{p,n,t} \leq C \times M[n], \ \forall \ n, t \tag{4.7}$$

$$t_{p,n} X_{p,n,t} \leq C \times M_p[n], \ \forall \ p, n, t \tag{4.8}$$

$$X_{p,n,t}, I_{p,n,t}, B_{p,t} \in \mathbb{R}^+, \ \forall p, n, t \tag{4.9}$$

where,

$b_p =$ backorder cost for product p per lot per time period,

$d_{p,t} =$ demand quantity of product p in time period t,

$t_{p,n} =$ lot processing time of product p at stage n,

$M_p[n] =$ number of machines at stage n qualified for product p,

$X_{p,n,t} =$ production quantity for product p at stage n in time period t,

$I_{p,n,t} =$ inventory quantity of product p at the end of time period t at (after) stage n,

$B_{p,t} =$ back order quantity of the product p in (the end of) time period t.

The objective (4.3) is to minimize the total backorder cost. Constraints (4.4) and (4.6) are inventory balance constraints. Constraints (4.5) say that the inventory at stage n in time period t will only be available to stage $n+1$ in time period $t+1$. Constraints (4.7) are the capacity constraints for one stage over all products, saying that total production time must be less than the total available machine capacity. Constraints (4.8) are the capacity constraints for one product over all the qualified machines at one stage, saying that the production time for one product must be less than the available qualified machine capacity.

Algorithm 1 LP Solution Conversion Algorithm

```
for $1 \le p \le P,\ 1 \le n \le N,\ 1 \le t \le T$ do
    if $X_{p,n,t} > 0$ then
        $F_{p,n,t} = X_{p,n,t} - \lfloor X_{p,n,t} \rfloor$
        if $F_{p,n,t} > 0$ then
            for $t \le \bar{t} \le T$ do
                if $X_{p,\ o,\ \bar{t}} \ge F_{p,n,t}$ then
                    $X_{p,\ o,\ \bar{t}} = X_{p,\ o,\ \bar{t}} - F_{p,n,t}$
                    $X_{p,n,t} = \lfloor X_{p,n,t} \rfloor + 1$
                    break
                else if $0 < X_{p,\ o,\ \bar{t}} < F_{p,n,t}$ then
                    $X_{p,\ o,\ \bar{t}} = 0$
                    $F_{p,n,t} = F_{p,n,t} - X_{p,\ o,\ \bar{t}}$
                end if
            end for
        end if
    end if
end for
```

Compared to the MILP formulation in Section 3, the above LP formulation of real world problem with 26 products, 3 stages, 50 machines, and over 1000 lots, can be solved with ILOG CPLEX11.2 on PC in less than one minute. However, the optimal solution to the LP formulation consists of fractional production quantities for each product at each stage. For the production plan, a *LPST* for each lot at each stage is needed. Thus the fractional optimal solution of the LP formulation will be converted to an integer solution first, and then the time period associated with the production quantity will be assigned as the *LPST* for all the lots. We use the LP Solution Conversion Algorithm in Algorithm 1 to integrate the fractional solution. The basic idea is to move part of the next non-zero production quantity in the time line earlier to make current production quantity integral. The *LPST*'s of all lots from the optimizer are used in the scheduler for the dynamic lot politicization (DLP) algorithm and the dynamic machine prioritization (DMP) algorithm.

4.2 Scheduler

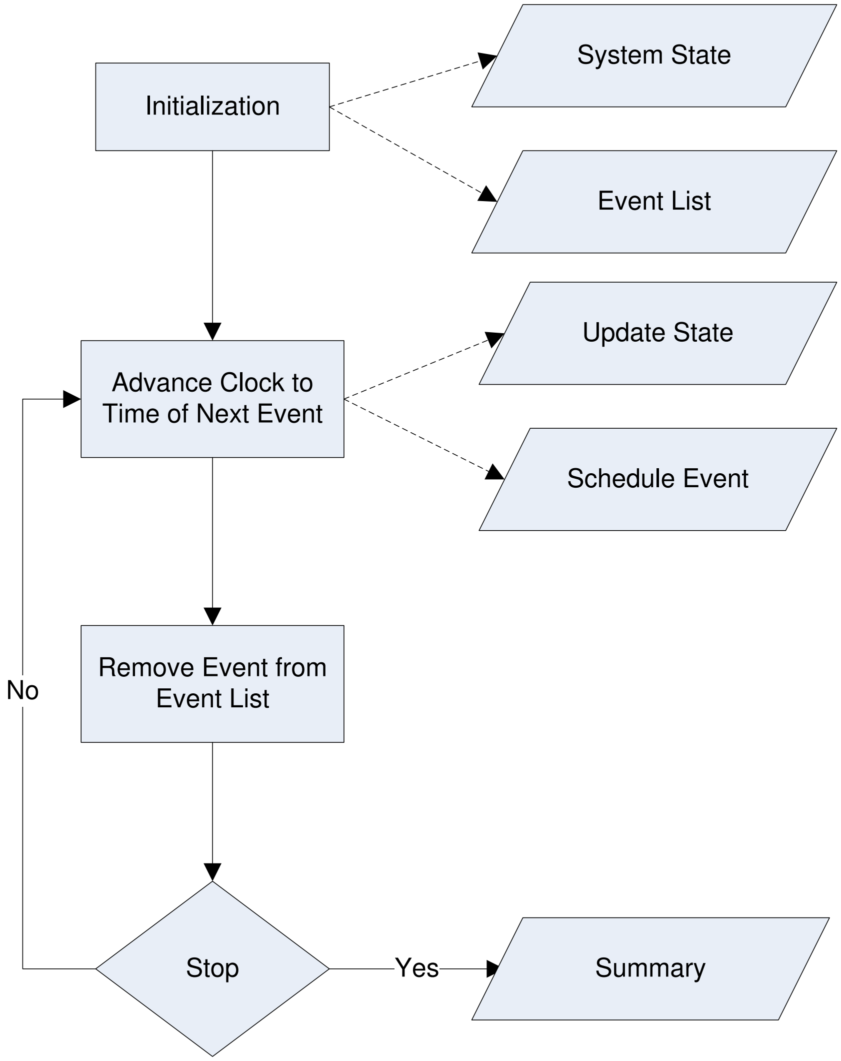


Figure 4.2: Discrete Event System

The scheduler is based on a deterministic discrete event system (DES) structure (Figure 4.2). There are two important data structures in a DES: event list and system state. Event list stores all the events scheduled to be happening in the future, and system state keeps track of the resources in the system. The clock in the DES moves forward when an event from the event list is executed. Future events will be generated during the execution and then put into the event list. There are six types of events in the scheduler: lot arrival to a stage, lot departure from a machine, end of a setup, end of a PM, end of an ET, and start of a time period. The following information is collected during the scheduling process: machine utilization, cycle time of each lot, queue length in front of each stage, etc. When a lot arrival event happens, the dynamic machine prioritization (DMP) rule in Algorithm 2 will be used to choose a machine from the stage to process this lot. The DMP rule prioritizes the machines at a stage based on the setup time and checks the eligibility of the setup/production based on the availability of setup staff (if setup needed), related customized factory rules (PM/ET schedules) and scheduling control rules (machine setup limit to be discussed later). If no machine is available or eligible, the lot will be waiting in the queue. It should be noted that before every lot processed, the scheduler will check the eligibility of the production and/or setup according to the following three criteria: (1) whether there is an available staff to perform the setup (if a setup is needed), (2) whether the number of machines setup for the product at this stage is less than the machine setup limit for the product at the stage, and (3) whether the production and/or setup will violate any PM or ET schedule. The machine setup limit is an adjustable parameter in the scheduler, which is used to control the number of setups in the scheduling process. When a lot departure event happens, a machine becomes idle and the dynamic lot prioritization (DLP) rule in Algorithm 3 will be used to choose a lot from the queue. The DLP prioritizes the lots in a queue based on their $LPST$'s and the setup time, and at the same time checks the eligibility of the setup/production. When an end of setup/PM/ET event happens, a machine as well as a setup staff become available, and thus all the idle machines in the system will be scheduled using the DLP rule. In the second row of the DLP rule in Algorithm 3, all the eligible and qualified lots are ranked based on their priorities and $LPST$'s. The ranking criteria are: (1) late lots are ranked based on their priorities, the higher the priority, the higher the rank; (2) all late lots are ranked higher than all early lots; (3) early lots are ranked based on their *LPST*'s, the earlier the *LPST*, the higher the rank. A lot is defined as late when its *LPST* is smaller than or equal to the current clock time in the system, and early when its *LPST* is larger than the current clock time in the system. Since the *LPST* of a lot is an important factor during the ranking process, the result from the DLP rule could be different when the clock time proceeds. As a result, at the beginning of each time period, all the idle machines in the system will be scheduled using the DLP rule too.

The main output of the DSS is a detailed schedule for each machine over the planning horizon with the exact start and finish time of each lot processing, setup, PM, or ET operation. Another output is a summary including the total execution time of the scheduling system, average utilization for each machine, average utilization for each staff, average cycle time for each product, total number of setups for each stage, average queue length for each stage, and shortages for each product.

4.3 Parameters

There are several adjustable parameters for the deterministic scheduling system, which could be used to optimize the DSS under different objectives or scenarios.

- Optimizer: LP optimizer or MRP optimizer.

- Lot Release Control: whether release all lots into the DSS at the beginning of the planning horizon or only release lots with *LPST*'s in a week at the beginning of the week, assuming weekly demands.

- Setup Control Level α_p: a multiplier used to set the number of machines allowed to be setup concurrently for product p at stage n, $S_{p,n} = \alpha_p \times \frac{D_p \times t_{np}}{\sum_p D_p \times t_{p,n}} \times M[n]$. So if there are already $S_{p,n}$ machines setup for product p at stage n, no

Algorithm 2 Dynamic Machine Prioritization Algorithm

```
search all machines at the stage
if there are idle machines qualified for the lot then
    rank all those machines by the setup time
    if the smallest setup time is positive then
        if the setup and production is eligible then
            execute the setup and production
            change the status of the machine to setup
            change the status of the staff to busy
            schedule an $end\_setup$ event
            schedule a $lot\_departure$ event
        else
            put the lot in the queue
        end if
    else
        if the production is eligible then
            execute the production
            change the status of the machine to produce
            schedule a $lot\_departure$ event
        end if
    end if
else
    put the lot in the queue
end if
```

additional machine can be setup to process product p at stage n until one or more of the $S_{p,n}$ machines are setup to run other products.

- WIP Control Level ω_p: a multiplier used to set the work-in-process(WIP) limit for product p in the system, $WIP_p = \frac{1}{\omega_p} \times \tilde{C_p} \times \tilde{\rho_p}$, in which $\tilde{C_p}$ is the average cycle time for product p with no WIP limit from the DSS, and $\tilde{\rho_p}$ is throughput rate of product p with no WIP limit from the DSS. When ω_p is zero, WIP_p is equal to ∞, which means there is no WIP control at all. Lots can not be released or advanced to a stage if a WIP limit would be exceeded. The WIP limits could be segmental, i.e. only from stage 3 to stage 6 out of 10 stages.

Algorithm 3 Dynamic Lot Prioritization Algorithm

```
search the queue for qualified and eligible lots
rank all those lots based on their priorities and $LPST$'s
if there is no qualified and eligible lot then
    if there is a qualified lot that can not be scheduled only because of conflicting a scheduled PM/ET then
        execute the PM/ET
        change the status of the machine from idle to PM/ET
        schedule a $PM/ET\_end$ event
    else
        leave the machine idle
    end if
else if the lot with the highest rank is an early lot then
    if there is a qualified late lot that can not be scheduled only because of conflicting a scheduled PM then
        execute the PM
        change the status of the machine from idle to PM
        schedule a $PM\_end$ event
    else
        execute the production
        change the status of the machine from idle to producing
        schedule a $lot\_depart$ event
    end if
else if the lot with the highest rank is a late lot then
    execute the production
    change the status of the machine from idle to producing
    schedule a $lot\_depart$ event
end if
```

CHAPTER 5

EXPERIMENT RESULTS

This section discusses the solvable size of the proposed BPSS formulation and the performance of the DSS through randomly generated small size and real size problem instances. The BPSS formulation was implemented in C++ and solved using CPLEX11.2 concert technology, compiled with Microsoft Visual C++. The DSS was implemented in C++, compiled with Microsoft Visual C++. Both programs were run on a PC with a Intel Xeon Dual Core 2.00 GHz, 2.00 GHz processor with 2 GB of RAM.

5.1 General Evaluation

Table 5.1: Toy Data Size

Number of Products P	$2,3,4$
Number of Stages S	$2,3$
Number of Weeks	2
Number of Periods in Each Week	5
Setup Time	0.5
Weekly Demand	$U(0,5)$
Number of machines at Each Stage	$U(1,5)$
Lot Processing Time	$U(0.5,1.5)$

Table 5.2: DSS Parameter Values

Optimizer	LP,MRP
Release Control	Y,N
Setup Control Level α	$1.0 \sim 5.0$ at step of 0.5
WIP Control Level ω	$0, \frac{1}{4}, \frac{1}{2}, 1, 2$

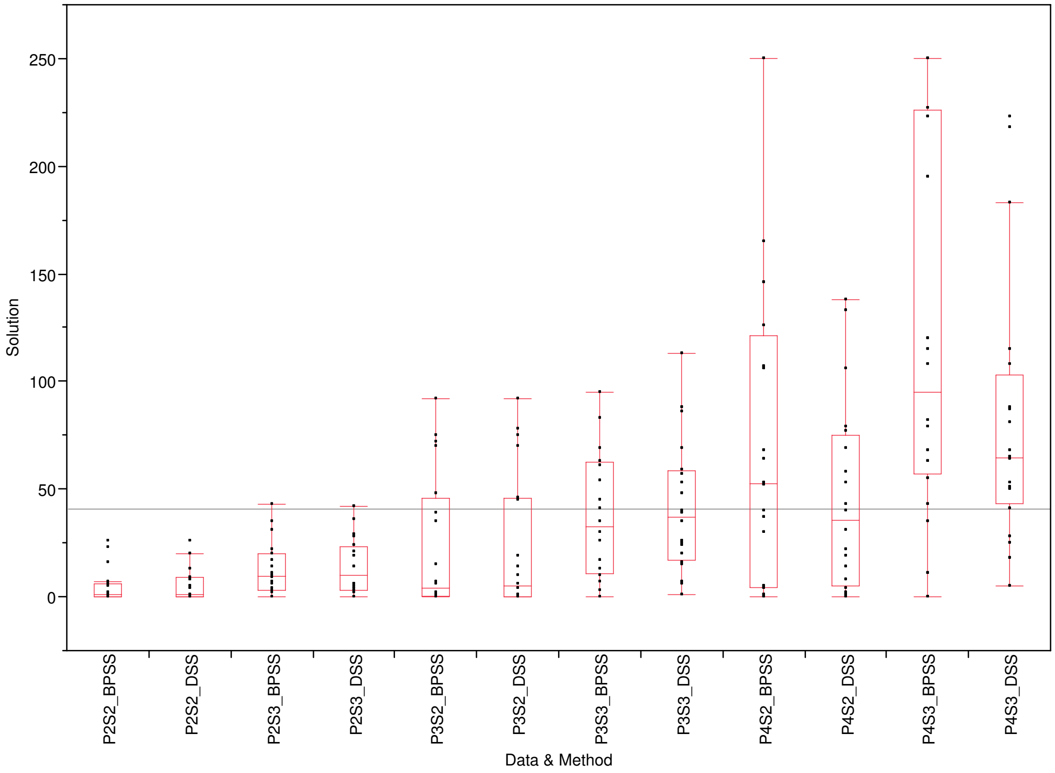
Twenty data sets are randomly generated according to each combination of factors for the small problems shown in Table 5.1, and then solved with both the BPSS and the DSS. For those small problems, there is no initial backorder for any product; only one operation is performed at each stage; all products follow the same route from the first stage to the last stage; all machines are qualified for all products; there is no initial WIP inventory in the system (start with an empty system); there is no PM/ET schedule; the product index represents the product priority, lower index meaning higher priority; the weight for the backorder of product p is defined as $b_p = P - p + 1$, in which P is the total number of products; every machine needs a setup for any product at the beginning, and the setup time is sequence independent. Problem cases are denoted as $PxSy$ for x products and y stages. Table 5.2 shows all the parameter values used in the DSS, and the DSS solutions are chosen as the best among all the parameter value combinations. The BPSS solutions were obtained with CPLEX11.2 with an optimality gap of 0.01, no time limit for $P2$ problems, and within 1 hour for $P3$ and $P4$ problems.

The summary of the BPSS and DSS solutions for small problems are shown in Figure 5.1, with Box-and-Whiskers plots of the solutions at each method (BPSS/DSS) and problem size (Product/Stage) combination in Figure 5.1a, and quartiles in Figure 5.1b. There are some $P4S2$ and $P4S3$ problems that BPSS could not find any feasible solution or only obtain very large feasible solutions within the 1 hour time limit. For those problems, the BPSS solutions are set to be 250 so that all solutions can fit in one figure with a reasonable scale. We observe from Figure 5.1 that for $P2$ and $P3$ problems the mean of BPSS solutions are slightly better than that of DSS solutions under the objective of minimizing prioritized backorder cost. However, for $P4$ problems the mean of BPSS solutions are worse than that of the DSS solutions. We did a matched pairs analysis of the BPSS solutions and DSS solutions of small problems grouped according to product and stage combination, as shown in Table 5.3. Matched pair analysis results in Table 5.3 show that the mean of DSS solution is 11.35 smaller than that of the BPSS solutions and the difference is significant. Across groups results shows the mean difference (DSS mean - BPSS mean) and mean mean ($\frac{\text{DSS mean + BPSS mean}}{2}$) for each group (product stage combination). Test across groups shows that the mean difference and mean mean between groups are significantly different, which verifies that the mean difference changes (decreases in magnitude) when problem size increases. As the problem size increases, the performance of DSS becomes better than the BPSS. It should be noted that in some cases, i.e. the 4th and 5th replicates of $P2S3$, the DSS solutions are even better than the corresponding optimal BPSS solutions. The reason is that the material is assumed to be moved at the end of every time period in BPSS while the material movement is continuous in the DSS (a lot is available to the next stage right after it is finished at current stage). We call this phenomenon the impact of discretization.

The solution times for both the BPSS and the DSS are summarized in Table 5.4 with median and standard deviation for each product and stage combination. It can be seen that the DSS has much smaller standard deviations compared to the BPSS across all problem sizes, and increases much slower as the problem size increases.

5.2 Offline Optimization of the DSS Parameters with Single Objective

Experimental design is used to evaluate important factors affecting the DSS performance and their interactions with a single objective of minimizing the total prioritized backorder cost. Those factors and their possible values to be evaluated in the experiment are listed in Table 5.5. Different numbers of products represent different levels of product mix. Three weekly demand distributions represent three demand scenarios of interest: low demand level with small deviation, low demand level with large deviation, and high demand level with small deviation. The machine utilization level θ is used to determine the number of machines at each stage n using $M[n] = \lceil \sum_p D_p \times t_{p,n}/(C \times \theta_n) \rceil$. In the experiment, all machines are assumed to



(a) Box-and-Whiskers Plots of Backorder Costs

Level	**Minimum**	**10%**	**25%**	**Median**	**75%**	**90%**	**Maximum**
P2S2_BPSS	0	0	0	1	6	22.3	26
P2S2_DSS	0	0	0	1	9	25.4	26
P2S3_BPSS	0	0	3	9.5	20	34.6	43
P2S3_DSS	0	0	3	10	23.25	35.3	42
P3S2_BPSS	0	0	0.25	4	45.75	74.7	92
P3S2_DSS	0	0	0	5	45.75	77.7	92
P3S3_BPSS	0	3.4	10.75	32.5	62.5	83	95
P3S3_DSS	1	6.1	17	37	58.5	87.8	113
P4S2_BPSS	0	0.1	4.25	52.5	121.25	241.5	250
P4S2_DSS	0	0.1	5	35.5	75	130.3	138
P4S3_BPSS	0	13.4	57	95	226	250	250
P4S3_DSS	5	18.7	43.25	64.5	103	214.5	223

(b) Quantiles of Backorder Costs

Figure 5.1: Solution Value Summary for Small Problem Instances

Table 5.3: Matched Pairs Analysis of Grouped Data for Small Problem Instance Solution Values

Matched Pairs Analysis			
DSS	35.0417	t-Ratio	-2.58722
BPSS	46.3917	DF	119
Mean Difference	-11.35	Prob $>|t|$	0.0109*
Std Error	4.38695	Prob $> t$	0.9946
Upper 95%	-2.6634	Prob $< t$	0.0054*
Lower 95%	-20.037		
N	120		
Correlation	0.68351		
Across Groups			
Product & Stage	**Count**	**Mean Difference**	**Mean Mean**
P2S2	20	1.35	5.425
P2S3	20	0.8	13.25
P3S2	20	0	23.25
P3S3	20	3.45	39.625
P4S2	20	-30.4	60.05
P4S3	20	-43.3	102.7
Test Across Groups	F **Ratio**	**Prob**$>F$	
Mean Difference	3.9761	0.0023*	Within Pairs
Mean Mean	17.4281	$<$.0001*	Among Pairs

be qualified for all products because the impact of machine qualification relationship on the performance of the DSS can be complicated and hard to define in the experimental design table. Then optimizer, release control, setup control level α, and WIP control level ω are configurable parameters for the DSS. The manufacturing system is based on a real semiconductor assembly and test factory, with 3 bottleneck stages, 3 operations, all products going through all operations, and all machines qualified for all products. The planning horizon is 2 weeks, with 84 2-hr time periods in each week. The setup times and processing times are generated

Table 5.4: Solution Time Summary for Small Problem Instances (seconds)

	P2S2		P2S3		P3S2		P3S3		P4S2		P4S3	
	BPSS	DSS	BPSS	DSS	BPSS	DSS	BPSS	DSS	BPSS	DSS	BPSS	DSS
Median	2.50	4.00	2.50	4.00	22.00	18.50	65.50	19.00	3506.50	18.50	848.50	19.50
Std Deviation	1367.44	0.31	996.83	0.37	1487.94	5.65	1367.76	5.62	1727.38	16.54	1687.04	8.14

Number of Products	$10,25,50$
Weekly Demand	$U(40,60),U(10,90),U(80,120)$
Machine Utilization θ	$60\%,90\%$
Optimizer	LP,MRP
Release Control	Y,N
Setup Control Level α	$1.0 \sim 5.0$ at step of 0.5
WIP Control Level ω	$0,\frac{1}{4},\frac{1}{2},1,2$

Table 5.5: Independent Variables in the Experiment Design (Single Objective)

according to Table 5.1.

An experiment is designed with the DOE customer design function in JMP8 to test all the main effects as shown in Table 5.5 and their two-factor interactions. The experiment requires 540 runs (a $\frac{1}{6}$ fractional design) with different combinations of the factor values, and 10 replicates were used. The Analysis of Variance and Effect Test results are shown in Table 5.6. RSquare of 0.71 means 71% of the variation in the response around the mean can be attributed to the terms in the model rather than to random error. All the main effects and the two-factor interactions are highly significant with P-value's less than 0.0001. Based on the fitted model, the Prediction Profiler in JMP8 recommends best configurations of the scheduler (Optimizer, Release Control, Setup Control Level, Control Level) which minimize the response variable under different scenarios (Number of Product, Weekly Demand, Machine Utilization), as shown in Table 5.7. The fitted model can also be used to recommend the configuration of the scheduler that minimizes the maximal or mean prioritized backorder cost over all scenarios, which are {LP, No Release Control, $\alpha = 0.5$, $\omega = \frac{1}{4}$} and {MRP, Release Control, $\alpha = 4$, $\omega = \frac{1}{2}$} respectively.

Note that the LP model outperforms the MRP approach for large problems. Likewise, release control is best in most cases and always best with a large number of products (50). The optimal setup control parameter varies but always exceeds the minimum feasible value of 1. In many cases values of 3.5 to 5 are best indicating that available capacity should be utilized rather than focusing on minimizing setups. In all but one case, the higher shop utilization level (90%) preferred as high or higher setup control level than the case of 60% utilization. While this may seem to waste time in extra setups, the exhaustive policy and due dates served to ensure that capacity was not wasted in setups but the higher setup level allowed the system to avoid wasting valuable capacity in the dynamic instances where certain products accumulated at stages with others not being available for processing. The best choice of WIP control was somewhat correlated with the mean demand level. At the higher level of 100 lots per product per period the best WIP control level was 1 or higher in 5 of 6 cases. With a mean demand of 50 lots per period per product, regardless of the number of products and size of the facility, a WIP control level of $\frac{1}{2}$ was best in 9 of 12 cases. The three cases with higher WIP control, meaning more restricted WIP levels, occurred with higher levels of demand variability (Uniformly distributed between 10 and 90 instead of 40 to 60).

5.3 Offline Optimization of the DSS Parameters with Multiple Objectives

In this section, experimental design is used to evaluate important factors affecting the DSS performance under multiple objectives. In this experiment, there are 3 stages and 4 operations. 2 operations are performed at the 3 stage. No setup is needed at the second stage. A minor setup is needed between the 2 operations at stage 3 for the same product. The planning period is 2 weeks and divided in to 168 2-hr time periods. The parameters and levels tested in the experiment are listed in Table 5.8. Data sets are randomly generated and the control parameters of DSS are set according to the values in the table. Exponential distribution is used to generate weekly demand. Product-machine qualification is considered in this experiment. The number of qualified machines for product p at stage n, $NQ_{p,n}$, is calculated

Table 5.6: Design of Experiment (Single Objective) Statistical Summary

Summary of Fit

RSquare	0.712727
RSquare Adj	0.704292
Root Mean Square Error	50783.52
Mean of Response	28989.14
Observations	5400

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob $> F$
Model	154	$3.36E+13$	$2.18E+11$	84.4992	0.0000
Error	5245	$1.35E+13$	$2.58E+09$		
C. Total	5399	$4.71E+13$			

Effect Tests

Source	N	DF	Sum of Squares	F Ratio	Prob $> F$
Number of Product (P)	2	2	4.17E+12	809.3092	<.0001
Weekly Demand (D)	2	2	1.12E+12	216.7478	<.0001
Machine Utilization (M)	1	1	2.80E+12	1084.732	<.0001
Optimizer (O)	1	1	2.60E+12	1007.006	<.0001
Release Control (R)	1	1	2.80E+12	1084.035	<.0001
Setup Control (S)	8	8	3.30E+11	15.9711	<.0001
WIP Control (W)	4	4	2.33E+11	22.5614	<.0001
P×D	4	4	8.28E+11	80.2933	<.0001
P×M	2	2	2.34E+12	454.5693	<.0001
P×O	2	2	2.06E+12	400.0243	<.0001
P×R	2	2	2.47E+12	478.756	<.0001
P×O	16	16	4.20E+11	10.1707	<.0001
P×W	8	8	2.69E+11	13.0305	<.0001
D×M	2	2	4.44E+11	86.0589	<.0001
D×O	2	2	8.37E+11	162.2237	<.0001
D×R	2	2	5.54E+11	107.4433	<.0001
D×O	16	16	4.75E+11	11.5161	<.0001
D×W	8	8	4.06E+11	19.7001	<.0001
M×O	1	1	1.30E+12	502.9219	<.0001
M×R	1	1	1.67E+12	649.2165	<.0001
M×O	8	8	3.20E+11	15.5078	<.0001
M×W	4	4	1.43E+11	13.8729	<.0001
O×R	1	1	2.59E+12	1004.306	<.0001
O×O	8	8	9.62E+10	4.6613	<.0001
O×W	4	4	1.34E+11	12.9555	<.0001
R×O	8	8	1.19E+11	5.7581	<.0001
R×W	4	4	2.31E+11	22.3957	<.0001
O×W	32	32	1.14E+12	13.8229	<.0001

Table 5.7: Recommended Configuration Under Each Scenario (Single Objective)

Num. of Product	Weekly Demand	Machine Utilization	Optimizer	Release Control	Setup Control	WIP Control
10	U(40,60)	60%	MRP	Y	4	1/2
10	U(40,60)	90%	MRP	Y	3.5	1/2
10	U(10,90)	60%	LP	N	1.5	0
10	U(10,90)	90%	MRP	Y	5	2
10	U(80,120)	60%	LP	N	1.5	1
10	U(80,120)	90%	LP	Y	5	2
25	U(40,60)	60%	MRP	Y	4	1/2
25	U(40,60)	90%	LP	Y	4	1/2
25	U(10,90)	60%	MRP	Y	4	1/2
25	U(10,90)	90%	LP	Y	4	1/2
25	U(80,120)	60%	LP	N	1.5	1
25	U(80,120)	90%	LP	Y	5	2
50	U(40,60)	60%	LP	Y	3.5	1/2
50	U(40,60)	90%	LP	Y	3.5	1/2
50	U(10,90)	60%	LP	Y	5	2
50	U(10,90)	90%	LP	Y	5	2
50	U(80,120)	60%	LP	Y	2	1/4
50	U(80,120)	90%	LP	Y	3	1

using Equation (5.1) as ϕ_p times the minimal number of machines needed, which is the total demand, $D_{p,n}$, times processing time, $t_{p,n}$, divided by single machine capacity, 168.

$$NQ_{p,n} = \phi_p \times D_p \times t_{p,n}/168 \tag{5.1}$$

The load share for product p on each qualified machine at stage n, $LS_{p,n}$, is calculated as $LS_{p,n} = D_p \times t_{p,n}/NQ_{p,n}$. $NQ_{p,n}$ load shares of product p are assign for machines at stage n with most available capacity iteratively and then the available capacity of the assigned machine is updated (minus the load share) after each iteration. Plan, release control, setup control level, and WIP control level are defined in Section 4.3. The tested objectives are shown in Table 5.9. The first objective is to minimize the runtime (sec) of the DSS. The next three objectives are to minimize the total number of setups for operations 1, 3, and 4. The fourth objective is to minimize the weighted cycle time over all lots during the planning period. The fifth objective is to maximize the total production during the planning period. The last three objectives are to minimize the total week 1 inventory, total week 1 shortage, and total week 2 shortage.

Table 5.8: Independent Variables in the Experimental Design (Multiple Objectives)

Number of Products P	10, 25
Mean Weekly Demand ${\mu_p}^a$	50 lots, 100 lots
Machine Utilization θ_n	60%, 90%
Qualification Ratio ${\phi_p}^b$	1.1, 1.55, 2.0
Plan	MRP, LP
Release Control	Yes, No
Setup Control Level α	1.0, 1.2, 1.5, 2.0
WIP Control Level ω	0, 1, 2/3

[a] mean of the Exponential distribution

[b] num. of qualified machines/num. of machines required

Table 5.9: Responses in the Experimental Design (Multiple Objective)

Response Name	**Response Goal**
Runtime (sec)	Minimize
Setup for Op1	Minimize
Setup for Op3	Minimize
Setup for Op4	Minimize
Weighted cycle time	Minimize
Total Production	Maximize
Total week 1 inventory	Minimize
Total week 1 shortage	Minimize
Total week 2 shortage	Minimize

The 8 experimental factors in Table 5.8 are used to design 96 production scenarios in JMP 8.0, and 10 test problems are randomly generated for each scenario. In total, 960 problems are run in the DSS and all 9 responses in Table 5.9 are collected for each problem. A statistical summary of responses is shown in Table 5.10. It can be seen from the statistical summary that different values of the control parameters in DSS make big differences on the responses.

Table 5.10: Statistical Summary of Responses (Multiple Objectives)

Response Name	**Min**	**Median**	**Max**
Runtime (sec)	0.109	1.031	19.704
Setup for Op1	4	55	212
Setup for Op3	36	310	1439
Setup for Op4	41	293	1333
Weighted cycle time	5.79277	18.1734	49.1437
Total Production	886	2677	6959
Total week 1 inventory	0	133	1921
Total week 1 shortage	0	147	1613
Total week 2 shortage	0	67	1592

Each response is fitted with all the parameters using Least Squares Fit in JMP 8.0. A desirability function $f()$ could be assigned to each response, with $f(\text{min}) = 0, f(\text{median}) = 0.5, f(\text{max}) = 1$. Then a weight between 0 and 1 is assigned to the desirability function of each response with the summation of all weights equal to 1. At the end, the total weighted desirability over all responses is defined as the weighted sum of all desirability functions. After the desirability functions and weights are set, parameter values maximizing the total weighted desirability are suggested by JMP 8.0 based on the fitted models. Table 5.11 shows five different sets of weights and the suggested parameter values maximizing the overall weighted desirability. From this table, it can be seen that some suggested parameter values are sensitive to the weights. In the future, a robustness analysis of the suggested values would be very meaningful.

Table 5.11: Suggested Parameter Values (Multiple Objectives)

Client Weights					
Runtime	0.11	0	0	0	0
Setup for O1	0.11	0.1	0	0.33	0
Setup for O3	0.11	0.1	0	0.33	0
Setup for O4	0.11	0.1	0	0.33	0
Weighted Cycle Time	0.11	0.2	0	0	1
Total Production	0.11	0	0	0	0
Total Week 1 Inventory	0.11	0.1	0	0	0
Total Week 1 Shortage	0.11	0.2	0.4	0	0
Total Week 2 Shortage	0.11	0.2	0.6	0	0
Optimal Parameter Value					
Number of Products P	10	10	10	10	25
Mean Weekly Demand μ_p	100	50	100	50	100
Machine Utilization θ_n	60%	60%	60%	60%	60%
Qualification Ratio ϕ_p	1.1	1.1	2.0	1.55	2.0
Plan	LP	LP	MRP	MRP	LP
Release Control	Yes	Yes	No	No	Yes
Setup Control Level α_p	1.5	1.5	1.2	2.0	2.0
WIP Control Level ω_p	2/3	2/3	1	0	1

In a real factory, number of products, mean weekly demand, and machine utilization in Table 5.8 are not controllable. In this case, the values of those three parameters are fixed first, and then the other parameter values are suggested by JMP 8.0 to maximize the total weighted desirability. The results using the second set of weights in Table 5.11 with 25 products are shown in Table 5.12. From this table, it can be seen that the suggested parameter values are sensitive to the three fixed parameter values too. In both Table 5.11 and Table 5.12, LP is always better with release control and MRP is always better with no release control.

5.4 Summary

In this research, we propose a new mixed integer linear programming (MILP) formulation and a deterministic scheduling system for medium term production scheduling in a semiconductor back-end factory. The objective is to minimize pri-

Table 5.12: Suggested Parameter Values with Three Fixed Parameters (Multiple Objectives)

Client Weights				
Runtime	0	0	0	0
Setup for O1	0.1	0.1	0.1	0.1
Setup for O3	0.1	0.1	0.1	0.1
Setup for O4	0.1	0.1	0.1	0.1
Weighted Cycle Time	0.2	0.2	0.2	0.2
Total Production	0	0	0	0
Total Week 1 Inventory	0.1	0.1	0.1	0.1
Total Week 1 Shortage	0.2	0.2	0.2	0.2
Total Week 2 Shortage	0.2	0.2	0.2	0.2
Fixed Parameter				
Number of Products P	25	25	25	25
Mean Weekly Demand μ_p	50	50	100	100
Machine Utilization θ_n	60%	90%	60%	90%
Optimal Controllable Parameter				
Qualification Ratio ϕ_p	1.1	2.0	2.0	2.0
Plan	LP	MRP	LP	LP
Release Control	Yes	No	Yes	Yes
Setup Control Level α_p	1.2	1.5	2.0	1.0
WIP Control Level ω_p	1	$2/3$	0	0

oritized tardiness with a model of relatively high fidelity to the actual factory. The MILP formulation and the DSS are compared by solving randomly generated small problem instances. The solution time of the MILP formulation can be long even for a small problem, and the optimal solution to the MILP formulation can be worse than the best DSS solution due to the impact of discretization. On the other hand, the DSS solution time is relatively small and consistent, and by adjusting the parameter values the best DSS solution quality is satisfactory (50% of the time equal to or better than the MILP optimal solution). The behavior of the DSS and the best configurations under different scenarios are evaluated through experimental design using randomly generated large problem instances.

In the future, decomposition techniques can be used to develop a heuristic converging to the optimal solution. The impact of the machine-product qualification relationship on the scheduling process as well as on the DSS performance would be another interesting problem to consider.

CHAPTER 6

STOCHASTIC MACHINE QUALIFICATION OPTIMIZATION

In order to process a product in a semiconductor back-end facility, a machine needs to be qualified first by having a product-specific software program installed on it. Then the required tool set must be available and attached on the machine while it is processing the product family. In general not all machines are qualified to process all products due to the high machine qualification cost and tool set availability. The machine qualification decision affects future capacity allocation in the facility and subsequently affects daily production schedule. To balance the tradeoff between current machine qualification costs and future backorder costs with uncertain demand, a stochastic product-machine qualification optimization model is proposed in this paper. The L-shaped method and acceleration techniques are proposed to solve the stochastic model. Computational results are provided to show the necessity of the stochastic model and the performance of different solution methods.

6.1 Introduction

The semiconductor manufacturing process consists of two main parts: the front-end process and the back-end process. The front-end process, also known as wafer fabrication, typically has a small number of products and very complex reentrant product flow. In contrast, the back-end process, also known as assembly and test, typically has hundreds or thousands of different products and relatively linear product flow. The research presented in this paper focuses on the back-end process. In a semiconductor back-end facility, each machine has to be configured for each of the products it will process in the future. This configuration (machine qualification) process includes installing and testing a software program for each product on the machine. Due to the wide product mix (i.e. thousands of products) in the semiconductor industry, if all machines were to be qualified for all products, the machine qualification process could take considerable time and engineering resource, thus incurring a high nonnegligible machine qualification cost. Meanwhile, not all machines are technologically capable of being qualified for all products. Because of short product life cycles and fast development of new products in the semiconductor industry, new machines may need to be procured frequently for new products. As a result, machines that perform the same operation could belong to different machine types/generations, with each type/generation only being able to be qualified for a subset of products. In addition, the product-machine qualification decision affects the capacity planning decision and subsequently the daily production schedule in the future. Poor product-machine qualification decision could cause shortages by not qualifying enough machines for a given product, or machine utilization imbalance by qualifying too many products on a small subset of machines. Overqualification may also complicate scheduling decisions and lead to misallocation of capacity. In this paper, a mixed integer linear programming model (MILP) is first proposed to minimize product-machine qualification cost while considering future production scheduling. As the last part of the semiconductor manufacturing system, on time delivery of customer orders is generally the most important goal for the back-end process. Hence the objective of the MILP is set to minimize the weighted product-machine qualification costs and future backorder costs with a higher weight on the latter. Due to computational limitation and demand forecast data availability, the production scheduling horizon in the model is set to be a medium term (e.g. several weeks). In addition, the product demand is represented by a random distribution to reflect the uncertainty.

Based on the literature review in Section 2.4, none of the papers integrates the future production planning and scheduling of a multi-stage manufacturing system in their machine qualification optimization models. On the other hand, machine qualification decisions have a critical long-term impact on the future production planing and scheduling. Furthermore, the interaction between qualification decisions for different stages impacts delivery performance. In this paper, a stochastic mixed integer linear programming model is proposed to optimize product-machine qualification in a multi-stage manufacturing system while considering future production scheduling with demand uncertainty. In the following section, we define the problem first and then propose a deterministic model.

6.2 Problem Statement

The back-end facility has multiple stages and parallel machines at each stage. Products are processed in lots with a product-specific number of units in each lot. Setup times are sequence-dependent and not included in the lot processing time. However, setup times are not considered explicitly in the model. Instead, the setup times are modeled by decreasing the machine capacity by a certain percentage based on historical machine utilization data. Product-machine qualification is considered in the model, and thus only qualified machines can process a given product at a given stage. Initial product-machine qualification in the model could be empty or given by an existing configuration. The objective of the model is to balance machine qualification costs and future backorder costs. The time horizon of future production scheduling in the model is limited to a medium term (i.e. a couple of weeks). The scheduling horizon is divided into small time buckets to model the movement of lots between stages. Meanwhile, the production quantity of each product on each machine will be scheduled for each time bucket. A mixed integer linear programming (deterministic) model is proposed first in this section.

The definition and notation of the elements for the deterministic machine qualification optimization (***D*-MQO**) model are listed below.

Notation:

P: number of products, with index p

N: number of stages, with index n

$M[n]$: number of unrelated machines at stage n, with index m

T: number of time periods in the production scheduling horizon, with index t

C: capacity of a machine in each time period ($C_{n,m,t}$ if it is machine and time period dependent)

A: available percentage of machine capacity in each time period ($1-A$ percent of machine capacity is reserved for setup activities)

$B_{p,0}$: initial back order quantity of product family p

$I_{p,n,0}$: initial inventory of product p at (after) stage n

b_p: backorder cost per lot per time period for product p

$d_{p,t}$: demand quantity for product p at the end of time period t in lots

$t_{p,n,m}$: lot processing time of product p on machine m at stage n

$c_{p,n,m}$: cost of qualifying machine m at stage n for product p

S_Q : a set of (p,n,m)'s with machine m at stage n initially qualified for product p

$\overline{S_Q}$: the complement of set S_Q

Decision Variables:

$X_{p,n,m,t} \in \mathbb{R}^+$: production quantity for product p in time period t on machine m at stage n

$I_{p,n,t} \in \mathbb{R}^+$: inventory quantity of product p at the end of time period t after stage n

$B_{p,t} \in \mathbb{R}^+$: back order quantity of the product p at the end of time period t

$Q_{p,n,m} \in \mathbb{B}$: 1 if machine m at stage n is recommended to be qualified for product p, 0 otherwise

Deterministic Machine Qualification Optimization Model (*D*-MQO)

$$min \quad \sum_{(p,n,m)\in\overline{S_Q}} c_{p,n,m}Q_{p,n,m} + \sum_{p,t} b_p B_{p,t} \tag{6.1}$$

$$s.t. \quad I_{p,n,t-1} + \sum_m X_{p,n,m,t} - \sum_m X_{p,n+1,m,t} = I_{p,n,t}, \ \forall \ p, n < N, t \tag{6.2}$$

$$I_{p,N,t-1} - B_{p,t-1} + \sum_m X_{p,N,m,t} - d_{p,t} = I_{p,N,t} - B_{p,t}, \ \forall \ p, t \tag{6.3}$$

$$\sum_m X_{p,n+1,m,t} \leq I_{p,n,t-1}, \ \forall \ p, n < N, t \tag{6.4}$$

$$\sum_p t_{p,n,m} X_{p,n,m,t} \leq C \cdot A, \ \forall \ n, 1 \leq m \leq M[n], t \tag{6.5}$$

$$t_{p,n,m} X_{p,n,m,t} \leq C Q_{p,n,m}, \ \forall \ p, n, m, t \tag{6.6}$$

$$Q_{p,n,m} = 1, \ \forall \ (p,n,m) \in S_Q \tag{6.7}$$

$$X_{p,n,m,t}, I_{p,n,t}, B_{p,t} \in \mathbb{R}^+, \ \forall \ p, n, m, t \tag{6.8}$$

$$Q_{p,n,m} \in \mathbb{B}, \ \forall \ p, n, m \tag{6.9}$$

The objective (6.1) is to minimize the total machine qualification and backorder costs. Constraints (6.2) are the inventory balance constraints for every product at every stage, except for the last stage, in each time period. They indicate that the inventory quantity at the end of period t must equal to the beginning inventory plus production at stage n in period t minus consumption at the next stage $n+1$ in period t. Constraints (6.3) are the inventory balance constraints for every product at the last stage in each time period. They are similar to constraints (6.2) except that the consumption at the next stage $n+1$ in period t is replaced by demand at the end of period t. Backorders are allowed but incur cumulative backorder costs as shown in the objective expression (6.1). Constraints (6.4) are the material availability constraints, which state that the production quantity at stage n in period t must be less than the inventory quantity at the previous stage $n-1$ at the end of period $t-1$. If a lot can flow through more than one stage in one time period, the RHS's of constraints (6.4) can be expanded to include production at one or more prior stages. Constraints (6.5) are the capacity constraints for every machine in each time period, which state that the total production time over all products must be less than the available machine capacity after setup time reservation. Constraints (6.6) are the machine qualification constraints, which state that production quantity $X_{p,n,m,t}$ is zero unless machine m at stage n is recommended to be qualified for product p. Constraints (6.7) define the initial qualification for machine m at stage n already qualified for product p. Constraints (6.8) and (6.9) are the positive and binary constraints for decision variables.

The model could be easily extended to include different process routes for different products and material handling time between stages by slightly modifying the subscripts. For example, instead of $X_{p,n+1,m,t}$, $X_{p,n+2,m,t}$ should be used in constraints (6.2) and (6.4) if product p skips stage n+1. If there is more than one operation performed at one stage, the stage subscript n can be substituted by operation subscript o in constraints (6.2), (6.3), and (6.4). Then in constraints (6.5) and (6.6), all the operations that could be performed on machine m at stage n should be considered in the left hand side. The material handling time for product p between stage n and stage n+1 is added on the subscript t of all $X_{p,n+1,m,t}$'s in constraints (6.2) and (6.4). If only bottleneck stages are modeled in the above formulation, which is possible when there are too many non-bottleneck stages in the manufacturing system, the material handling time can be further extended to include product-dependent delay times at non-bottleneck stages.

In the objective function (6.1), the total machine qualification cost is a one-time cost and the total backorder cost over the production scheduling period (e.g. a week) actually represents recurring costs. In addition, since our most important goal is to satisfy all demand, with minimizing machine qualification costs being the secondary objective, the machine qualification cost rates $c_{p,n,m}$'s are set to be very small compared to the backorder cost rates b_p's. In an alternative formulation, we can limit the total backorder cost $\sum_{p,t} b_p B_{p,t}$ to a constant in the constraints and minimize machine qualification cost. With the alternative formulation, we could generate a tradeoff curve between the total backorder cost limit and the total machine qualification cost.

The medium-term production scheduling considered in the above formulation is a snapshot of future production scheduling. Therefore it should reflect a steady state of the production system. If we start with an empty system in the above formulation, the start-up effect could give us a non-optimal machine qualification for future steady state production scheduling. As a result, Little's law [Little, 1961] is used to estimate initial inventory quantities in the above formulation in a steady state system:

$$I_{p,n,0} = \bar{t}_{p,n} \cdot \bar{d}_p, \ \forall p, n \tag{6.10}$$

where $I_{p,n,0}$ is the initial inventory of product p at (after) stage n, $\bar{t}_{p,n}$ is the average lot processing time of product p at stage n, and $\bar{d}_p$ is the average demand rate of product p. Average waiting time could be included in $\bar{t}_{p,n}$ if desired. To keep the production system in the steady state, the ending inventory quantities at all stages should be greater than or equal to the corresponding starting inventory quantities or otherwise defined minimum. Therefore the following constraints should be added to the formulation during realization.

$$I_{p,n,T} \geq I_{p,n,0}, \ \forall p, n \tag{6.11}$$

In the above deterministic model, the demand quantities $d_{p,t}$'s used in the production scheduling are assumed to be certain at the time when the machine qualification decisions are made. However, the demand quantities are usually based on forecast and thus uncertain in real world. Therefore, a stochastic model is proposed in the following section to consider the demand uncertainty.

6.3 Stochastic Machine Qualification Optimization Model (***S*-MQO**)

Machine qualification is usually a long term factory configuration decision which incurs nonnegligible time and monetary costs. It affects capacity allocation and thus daily production schedules directly. In our model, the machine qualification decisions are integrated with medium term production scheduling. The objective is to minimize the total machine qualification costs and backorder costs. Since the demand data used in the production scheduling are uncertain, a stochastic machine qualification optimization model is proposed in this section with the objective of minimizing total machine qualification costs and expected backorder costs. The purpose of this stochastic model is to find a robust product-machine qualification matrix at minimal qualification cost. Cost parameters need to be assigned to machine qualification operations at now and backorders in the future. Those parameters should be determined carefully considering that minimizing backorders is the primary objective and minimizing qualification costs is the secondary objective.

A two-stage stochastic machine qualification model is presented below. The demand is represented by a random vector $\xi = (d_{0,0},...,d_{P,T})^T$, with $d_{p,t}$ being the demand quantity of product p in period t. The objective (6.12) is to minimize the summation of total machine qualification costs $\sum_{(p,n,m)\in\overline{S_Q}} c_{p,n,m}Q_{p,n,m}$ and expected total backorder costs $\mathbb{E}[O(X,I,B,\xi)]$ over all possible demand scenarios.

$$min \quad \sum_{(p,n,m)\in\overline{S_Q}} c_{p,n,m}Q_{p,n,m} + \mathbb{E}[O(X,I,B,\xi)] \tag{6.12}$$

$$s.t. \quad Q_{p,n,m} = 1, \ \forall \ (p,n,m) \in S_Q \tag{6.13}$$

$$Q_{p,n,m} \in \mathbb{B}, \ \forall \ p,n,m \tag{6.14}$$

$O(X,I,B,\xi)$ is the optimal value of the following production scheduling subproblem given a machine qualification matrix Q and a demand scenario ξ_s:

$$min \quad \sum_{p,t} b_p B_{p,t} \tag{6.15}$$

$$s.t. \quad I_{p,n,t-1} + \sum_m X_{p,n,m,t} - \sum_m X_{p,n+1,m,t} = I_{p,n,t}, \ \forall\ p, n < N_p, t \tag{6.16}$$

$$I_{p,N_p,t-1} - B_{p,t-1} + \sum_m X_{p,N_p,m,t} - d_{p,t}(\xi_s) = I_{p,N_p,t} - B_{p,t}, \ \forall\ p,t \tag{6.17}$$

$$\sum_m X_{p,n+1,m,t} \leq I_{p,n,t-1}, \ \forall\ p, n < N_p, t \tag{6.18}$$

$$I_{p,n,T} \geq I_{p,n,0}, \ \forall p, n \tag{6.19}$$

$$\sum_p t_{p,n,m} X_{p,n,m,t} \leq C \cdot A, \ \forall\ n,m,t \tag{6.20}$$

$$t_{p,n,m} X_{p,n,m,t} \leq C Q_{p,n,m}, \ \forall\ p,n,m,t \tag{6.21}$$

$$X_{p,n,m,t}, I_{p,n,t}, B_{p,t} \in \mathbb{R}^+, \ \forall\ p,n,m,t \tag{6.22}$$

The first-stage decision variables $Q_{p,n,m}$'s are determined before the realization of random demand vector ξ. The second-stage decision variables $X_{p,n,m,t}$'s, $I_{p,n,t}$'s, and $B_{p,t}$'s are determined based on the first-stage decision and the realized demand vector ξ_s.

6.4 Deterministic Equivalent Formulation

If the random demand vector ξ can be represented or approximated by a discrete distribution with possible demand scenarios $(\xi_1, ..., \xi_S)$ and associated probabilities $(P(\xi_1), ..., P(\xi_S))$, the previous two-stage stochastic model could be rewritten as the following deterministic equivalent formulation. $X_{p,n,m,t}(\xi_s)$'s, $I_{p,n,t}(\xi_s)$'s, $B_{p,t}(\xi_s)$'s are the second-stage decision variables for demand scenario ξ_s.

$$min \sum_{p,t,s} P(\xi_s) b_p B_{p,t}(\xi_s) + \sum_{(p,n,m) \in \overline{S_Q}} c_{p,n,m} Q_{p,n,m} \tag{6.23}$$

$$s.t. \ I_{p,n,t-1}(\xi_s) + \sum_m X_{p,n,m,t}(\xi_s) - \sum_m X_{p,n+1,m,t}(\xi_s) = I_{p,n,t}(\xi_s), \ \forall\ p,$$

$$n < N_p, t, s \tag{6.24}$$

$$I_{p,N_p,t-1}(\xi_s) - B_{p,t-1}(\xi_s) + \sum_m X_{p,N_p,m,t}(\xi_s) - d_{p,t}(\xi_s) = I_{p,N_p,t}(\xi_s)$$

$$- B_{p,t}(\xi_s),\ \forall\ p,t,s \tag{6.25}$$

$$\sum_m X_{p,n+1,m,t}(\xi_s) \leq I_{p,n,t-1}(\xi_s),\ \forall\ p,n < N_p,t,s \tag{6.26}$$

$$I_{p,n,T}(\xi_s) \geq I_{p,n,0}(\xi_s),\ \forall p,n,s \tag{6.27}$$

$$\sum_p t_{p,n,m} X_{p,n,m,t}(\xi_s) \leq C \cdot A,\ \forall\ n,m,t,s \tag{6.28}$$

$$t_{p,n,m} X_{p,n,m,t}(\xi_s) \leq C Q_{p,n,m},\ \forall\ p,n,m,t,s \tag{6.29}$$

$$Q_{p,n,m} = 1,\ \forall\ (p,n,m) \in S_Q \tag{6.30}$$

$$X_{p,n,m,t}(\xi_s), I_{p,n,t}(\xi_s), B_{p,t}(\xi_s) \in \mathbb{R}^+,\ \forall\ p,n,m,t,s \tag{6.31}$$

$$Q_{p,n,m} \in \mathbb{B},\ \forall\ p,n,m \tag{6.32}$$

By solving the above deterministic equivalent formulation directly using a optimization solver (i.e. ILOG CPLEX), an optimal solution to the two-stage stochastic optimization problem (***S*-MQO**) can be obtained. The deterministic equivalent formulation is a mixed integer linear program. As a result, when there are a large number of demand scenarios, products, or machines, the deterministic equivalent formulation can be very difficult to solve. The L-shaped method and acceleration techniques are thus proposed to solve the deterministic equivalent formulation for large problem instances.

L-Shaped Method

The extensive form of the deterministic equivalent formulation has a block structure. Taking the dual of the extensive form, we can obtain a dual block-angular structure. Therefore, it is natural to exploit Dantzig-Wolf decomposition [Dantzig and Wolfe, 1960] on the dual or Bender's decomposition [Benders, 1962] on the primal. Van Slyke and Wets [1969] extend this method to take care of feasibility in stochastic programming, which is now called the L-shaped method. The classic

L-shaped method is first developed only for stochastic linear programs. A valid set of feasibility cuts and optimality cuts is known to exist in the continuous case, based on duality theory in linear programming. This knowledge forms the basis of the classic L-shaped method. Those cuts can also be used in the case where only some first-stage variables are integers, e.g. the ***S*-MQO** model. On the other hand, properties of general integer stochastic programs are scarce, and there is an absence of general efficient solution methods. The integer L-shaped method is the integration of the classic L-shaped method and branch-and-bound, during which optimality and feasibility cuts are added to LP relaxations. Since the ***S*-MQO** has binary first-stage variables and continuous second-stage variables, the classic L-shaped decomposition algorithm is chosen instead of the integer L-shaped method. The L-shaped method is briefly described below as it applies to our problem.

L-Shaped Method

Step 0 Set lower bound $LB = -\infty$ and upper bound $UB = \infty$. Set the iteration count $i = 0$.

Step 1 Solve the master problem for an optimal solution Q^i

$$LB = min \sum_{(p,n,m)\in\overline{S_Q}} c_{p,n,m}Q_{p,n,m} + \theta$$

$$s.t.\ Q_{p,n,m} = 1,\ \forall\ (p,n,m) \in S_Q$$

$$Q_{p,n,m} \in \mathbb{B},\ \forall\ p,n,m$$

$$\theta \geq \sum_{p,n,m} E^k_{p,n,m}Q_{p,n,m} + e^k, k = 1,2,...,i$$

Step 2 For $s = 1,...,S$, solve the following subproblem corresponding to Q^i and ξ_s

$$O(Q^i,\xi_s) = min \sum_{p,t} b_p B_{p,t} \qquad \text{Dual}$$

$$s.t.\ I_{p,n,0}+\sum_m X_{p,n,m,1}-\sum_m X_{p,n+1,m,1}=I_{p,n,1}, \forall\ p,n<N_p \qquad (\gamma_{p,n}(\xi_s))$$

$$I_{p,n,t-1}+\sum_m X_{p,n,m,t}-\sum_m X_{p,n+1,m,t}=I_{p,n,t}, \forall\ p,n<N_p,$$

$$1<t\leq T$$

$$I_{p,N_p,t-1}-B_{p,t-1}+\sum_m X_{p,N_p,m,t}-d_{p,t}(\xi_s)=I_{p,N_p,t}-B_{p,t},$$

$$\forall\ p,t \qquad (\mu_{p,t}(\xi_s))$$

$$\sum_m X_{p,n+1,m,1}\leq I_{p,n,0},\ \forall\ p,n<N_p \qquad (\sigma_{p,n}(\xi_s))$$

$$\sum_m X_{p,n+1,m,t}\leq I_{p,n,t-1},\ \forall\ p,n<N_p, 1<t\leq T$$

$$I_{p,n,T}\geq I_{p,n,0},\ \forall p,n \qquad (\varphi_{p,n}(\xi_s))$$

$$\sum_p t_{p,n,m}X_{p,n,m,t}\leq C\cdot A,\ \forall\ n,m,t \qquad (\pi_{n,m,t}(\xi_s))$$

$$t_{p,n,m}X_{p,n,m,t}\leq CQ^i_{p,n,m},\ \forall\ p,n,m,t \qquad (\rho_{p,n,m,t}(\xi_s))$$

$$X_{p,n,m,t}, I_{p,n,t}, B_{p,t}\in\mathbb{R}^+,\ \forall\ p,n,m,t$$

If $\sum_{(p,n,m)\in\overline{S_Q}} c_{p,n,m}Q^i_{p,n,m}+\sum_s P(\xi_s)O(Q^i,\xi_s)<UB$, update the upper bound.

Step 3 If $(UB-LB)/LB<\delta$, stop and return $Q=\{Q^i_{p,n,m}\}$ as the optimal solution and UB as the optimal objective value.

Step 4 For each $s=1,2,...,S$, compute the cut coefficients

$$E^{i+1}_{p,n,m}=\sum_s P(\xi_s)(\sum_t \rho_{p,n,m,t}(\xi_s)\cdot C_{n,m,t})$$

and

$$\begin{aligned} e^{i+1}=&\sum_s P(\xi_s)[-\sum_{p,n<N_p} I_{p,n,0}\cdot\gamma_{p,n}(\xi_s)+\sum_{p,n<N_p} I_{p,n,0}\cdot\sum_{p,t}\sigma_{p,n}(\xi_s)\\ &+\sum_{p,n} I_{p,n,0}\cdot\varphi_{p,n}(\xi_s)+\sum_p \mu_{p,1}(\xi_s)\cdot(d_{p,1}(\xi_s)-I_{p,N_p,0})\\ &+\sum_{p,t>1}\mu_{p,t}(\xi_s)\cdot d_{p,t}(\xi_s)+\sum_{n,m,t}\pi_{n,m,t}(\xi_s)\cdot C\cdot A]. \end{aligned}$$

Update $i = i + 1$ and go to Step 1.

In the L-shaped method, the master program solved in Step 1 provides a lower linear approximation for the function $\sum_s P(\xi_s)O(Q, \xi_s)$ through a continuous variable θ and optimality cuts $\theta \geq \sum_{p,n,m} E^k_{p,n,m} Q_{p,n,m} + e^k$, and therefore a lower bound LB for the objective function (6.23). The optimal solution Q^i obtained through the master program corresponds to a feasible solution for the stochastic program. It should be noted that in the first iteration $i = 0$, neither θ nor any optimality cut is included in the master problem. In Step 2, all S subproblems are solved using the optimal Q^i obtained from the master problem and corresponding demand scenario ξ_s. These S linear programs are solved independently, allowing for a computationally convenient decomposition. If all S subproblems are feasible, which in our case is always true since backorders are allowed in all subproblems, these subproblem solutions together with the master problem solution yield a upper bound UB of the original problem. When the upper bound UB and the lower bound LB are sufficiently close within a preset relative error term δ, we conclude optimality. Otherwise the dual optimal solutions of the subproblems are used to compute an optimality cut added in the master program in the next iteration. Only dual variables corresponding to constraints with positive right-hand-side values or positive coefficients of first-stage variables ($Q_{p,n,m}$'s) will affect the cut coefficients. Those dual variables are represented as the $\gamma_{p,n}$'s, $\mu_{p,t}$'s, $\sigma_{p,n}$'s, $\pi_{n,m,t}$'s, $\varphi_{p,n}$'s, and $\rho_{p,n,m,t}$'s in the parenthesis. It should be noted that the initial inventory quantities $I_{p,N_p,0}$'s at/after the last stage are assumed to be zero, because the demand quantities $B_{p,t}$'s can always be adjusted to make $I_{p,N_p,0}$'s zero. In Step 4, according to the duality theory the optimality cut $\sum_s P(\xi_s)O(Q, \xi_s) = E^{i+1}_{p,n,m} Q_{p,n,m} + e^{i+1}$ is exact for Q^i and is a lower linear approximate for all other feasible Q's.

In the classic L-shaped method, two types of cuts are added to the master problem: feasibility cuts and optimality cuts. Optimality cuts are computed in the previous algorithm in Step 4. Feasibility cuts are added if and only if the master solution in Step 1 is infeasible for certain subproblems in Step 2. Since backorders are allowed in our model, all feasible master problem solutions are feasible for all the subproblems. As a result, no feasibility cut is added in the algorithm.

Acceleration of The L-Shaped Method

The number of iterations in the L-shaped method for real world problem instances can be very large. To improve the convergence behavior of the L-shaped method, the following acceleration techniques are proposed.

Cut Disaggregation

In the standard L-shaped method, one optimality cut is added at each iteration, which approximates the expectation of the second-stage objective functions given the current first-stage solution. Instead of one cut, S optimality cuts could be added at each iteration to approximate individual second-stage objective functions. The optimality cut corresponding to demand scenario ξ_s at iteration i is represented by

$$\theta^s \geq \sum_{p,n,m} E^{s,i}_{p,n,m} Q_{p,n,m} + e^{s,i},$$

in which

$$E^{s,i}_{p,n,m} = \sum_t \rho^i_{p,n,m,t}(\xi_s) \cdot C_{n,m,t}$$

and

$$\begin{aligned} e^{s,i} = & - \sum_{p,n<N_p} I_{p,n,0} \cdot \gamma^i_{p,n}(\xi_s) + \sum_{p,n<N_p} I_{p,n,0} \cdot \sum_{p,t} \sigma^i_{p,n}(\xi_s) \\ & + \sum_{p,n} I_{p,n,0} \cdot \varphi^i_{p,n}(\xi_s) + \sum_p \mu^i_{p,1}(\xi_s) \cdot (d_{p,1}(\xi_s) - I_{p,N_p,0}) \\ & + \sum_{p,t>1} \mu^i_{p,t}(\xi_s) \cdot d_{p,t}(\xi_s) + \sum_{n,m,t} \pi^i_{n,m,t}(\xi_s) \cdot C \cdot A. \end{aligned}$$

In the $(i+1)th$ iteration, the master problem takes the following form.

$$
\begin{aligned}
min & \sum_{(p,n,m)\in\overline{S_Q}} c_{p,n,m}Q_{p,n,m} + \sum_s P(\xi_s)\theta^s \\
s.t. \; & Q_{p,n,m} = 1, \; \forall \; (p,n,m) \in S_Q \\
& Q_{p,n,m} \in \mathbb{B}, \; \forall \; p,n,m \\
& \theta^s \geq \sum_{p,n,m} E^{s,i}_{p,n,m} Q_{p,n,m} + e^{s,i}, k = 1,2,...,i, s = 1,2,...,S
\end{aligned}
$$

This approach is referred to as multicut L-shaped algorithm [Birge François and John, 1988]. In the multicut version, there is no information loss due to cut aggregation, thus providing a better approximation of the expectation of second-stage objective functions. Consequently, there are fewer iterations in the multicut L-shaped method. However, since more cuts are added at each iteration, the cost of the multicut algorithm is to solve larger master problems.

Qualification Cuts

In the early iterations of the standard L-shaped method there are very few cuts in the master problem. As a result, a minimal number of machines are qualified in the optimal solutions of the master problem, which results in large backorder quantities at the second-stage subproblems. To avoid such poor master problem solutions, information of the second-stage subproblems is integrated in the master problem. Qualification cuts are added in the master problem to impose a lower bound restriction on the number of machines to be qualified for each product at each stage.

The following formulation is defined as the single-scenario qualification subproblem for ξ_s $(1 \leq s \leq S)$.

$$
\begin{aligned}
min \; & P(\xi_s)\sum_{p,t} b_p B_{p,t}(\xi_s) + \sum_{(p,n,m)\in\overline{S_Q}} c_{p,n,m}Q_{p,n,m}(\xi_s) \\
s.t. \; & I_{p,n,t-1}(\xi_s) + \sum_m X_{p,n,m,t}(\xi_s) - \sum_m X_{p,n+1,m,t}(\xi_s) = I_{p,n,t}(\xi_s), \; \forall \; p, n < N_p, t
\end{aligned}
$$

$$I_{p,N_p,t-1}(\xi_s) - B_{p,t-1}(\xi_s) + \sum_m X_{p,N_p,m,t}(\xi_s) - d_{p,t}(\xi_s) = I_{p,N_p,t}(\xi_s)$$

$$-B_{p,t}(\xi_s),\ \forall\ p,t$$

$$\sum_m X_{p,n+1,m,t}(\xi_s) \leq I_{p,n,t-1}(\xi_s),\ \forall\ p,n < N_p,t$$

$$I_{p,n,T}(\xi_s) \geq I_{p,n,0}(\xi_s),\ \forall p,n$$

$$\sum_p t_{p,n,m} X_{p,n,m,t}(\xi_s) \leq C \cdot A,\ \forall\ n,m,t$$

$$t_{p,n,m} X_{p,n,m,t}(\xi_s) \leq C Q_{p,n,m}(\xi_s),\ \forall\ p,n,m,t$$

$$Q_{p,n,m} = 1,\ \forall\ (p,n,m) \in S_Q$$

$$X_{p,n,m,t}(\xi_s), I_{p,n,t}(\xi_s), B_{p,t}(\xi_s) \in \mathbb{R}^+,\ \forall\ p,n,m,t$$

$$Q_{p,n,m} \in \mathbb{B},\ \forall\ p,n,m$$

Let $\bar{B}^s_{p,t}(\xi_s)$'s be the optimal backorder quantities obtained from the single-scenario qualification subproblem for ξ_s $(1 \leq s \leq S)$ and $\bar{B}^o_{p,t}(\xi_s)$'s be the optimal backorder quantities obtained from the ***S*-MQO** model. When $c_{p,n,m} << P(\xi_s)b_p$ $(\forall p,n,m)$ holds, they must satisfy the following conditions:

$$\sum_{p,t} b_p \bar{B}^s_{p,t}(\xi_s) = \sum_{p,t} b_p \bar{B}^o_{p,t}(\xi_s),\ \forall\ s \tag{6.33}$$

Because both $P(\xi_s)\sum_{p,t} b_p \bar{B}^s_{p,t}(\xi_s)$ and $P(\xi_s)\sum_{p,t} b_p \bar{B}^o_{p,t}(\xi_s)$ are equal to the minimal total backorder cost in demand scenario ξ_s given that every machine is qualified for every product. Therefore, if $\bar{Q}^s(\xi_s)$ is the unique optimal machine qualification matrix obtained from the single-scenario qualification subproblem for ξ_s $(1 \leq s \leq S)$ and $\bar{Q}^o$ is an optimal machine qualification matrix obtained from the ***S*-MQO** problem, they must satisfy the following conditions:

$$\sum_m \bar{Q}^o_{p,n,m} \geq \sum_m \bar{Q}^s_{p,n,m}(\xi_s),\ \forall\ p,n \tag{6.34}$$

Conditions (6.34) hold only when the following two assumptions are both valid: $c_{p,n,m} << P(\xi_s)b_p$ $(\forall p,n,m,s)$ and each single-scenario qualification subproblem has a unique optimal machine qualification matrix. The first assumption $c_{p,n,m} << P(\xi_s)b_p$ $(\forall p,n,m,s)$ holds if the cost parameters $c_{p,n,m}$'s and b_p's are carefully chosen. Because there are usually multiple optimal solutions for real world applications, the second assumption usually does not hold. As a result, adding inequalities (6.34) in the master problem leads to a sub-optimal solution for the original ***S*-MQO** problem. However, if the first assumption holds, the expected total backorder costs over all scenarios should still be the same with or without inequalities (6.34). Adding inequalities (6.34) will decrease the number of iterations in the L-shaped method. Thus the tradeoff here is between the total machine qualification cost and the solution time of L-shaped method. Inequalities (6.34) are referred to as qualification cuts in this paper.

Relaxed Qualification Cuts

When the problem size increases, even the single-scenario qualification subproblem can be difficult to solve since it is a mixed integer linear program. In this case, we can solve the LP relaxation of the single-scenario qualification subproblem for an optimal continuous machine qualification matrix $\tilde{Q}^s$. Then a binary machine qualification $\bar{\bar{Q}}^s$ can be obtained using the following rule:

$$\begin{cases} \bar{\bar{Q}}^s = 1, & \tilde{Q}^s > \varepsilon \\ \bar{\bar{Q}}^s = 0, & \tilde{Q}^s \leq \varepsilon \end{cases}$$

where ε is a preset value between 0 and 1. A set of qualification cuts similar to inequalities (6.34) can be added using $\bar{\bar{Q}}^s$ instead of $\bar{Q}^s$. Those cuts are called relaxed qualification cuts. They require significantly less time for solving the (relaxed) single-scenario qualification subproblems. On the other hand, both optimal machine qualification cost and expected backorder cost with relaxed qualification cuts can be larger than those of the original ***S*-MQO** problem. Therefore, the tradeoff here is still between the solution quality and solution time.

6.5 Computational Experiments

In this section we will present a numerical experiment solving a 5-product problem instance with the proposed models and solution methods. First, the manufacturing system and demand information are introduced. Then the efficiencies of the two different stochastic solution methods for the *S*-MQO model will be discussed and compared using different numbers of scenarios. At the end, the solution quality of stochastic and deterministic models will be evaluated and thus compared through an optimization based scheduling system.

Data

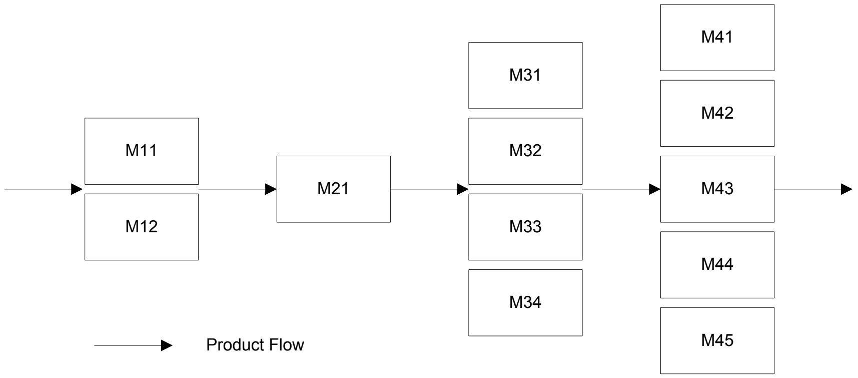


Figure 6.1: Manufacturing system description

The 5-product problem instance is based on a real semiconductor back-end facility with 4 bottleneck stages. Usually there are 20 to 30 processing stages in a back-end facility. However, including all those stages in the mathematical model results in a significantly larger formulation size. Therefore all the non-bottleneck stages are modeled as constant delays between bottleneck stages, as stated in Section 6.2. The delay time on a non-bottleneck stage is estimated by the average throughput time at this stage. It is assumed there are multiple identical parallel machines at each stage, as shown in Table 6.1. Every machine can be qualified

Table 6.1: Manufacturing System Description.

Number of products	5
Num. of bottleneck stages	4
Num. of machines	(2,1,4,5)
Stage 1 Processing Time	$U(1.00, 2.00)$
Stage 2 Processing Time	$U(0.10, 0.20)$
Stage 3 Processing Time	$U(2.00, 4.00)$
Stage 4 Processing Time	$U(2.00, 4.50)$

Table 6.2: Weekly Demand.

	60% Utilization	90% Utilization
Weekly demand	$U(5, 25)$	$U(5, 35)$
Weekly demand average	15	20
Weekly demand maximal	25	35

to process every product. The production scheduling horizon in the model is chosen to be 1 week, which is divided into 84 2-hr time buckets. All the times used in the experiments are in 2-hr units, e.g. processing time of 1.5 per lot in the experiment representing 3-hour per lot actual processing time. Two processing time distributions are used in the experiment to simulate production systems with approximately 60% and 90% machine utilizations. Processing times of all products at the same stage are randomly generated based on the same distribution, as shown in Table 6.1. Although products are allowed to have different processing routes or skip certain stages in the proposed models, all products are assumed to go through all stages in the same linear sequence in the experiment. Customer orders or product types can be assigned with different priorities through their backorder cost rates (per lot per 2-hr time bucket), e.g. important orders or product types with higher backorder cost rates. However in the experiment, all product types and lots are assumed to have the same priority for simplicity, therefore the same backorder cost rate. The initial product-machine qualification matrix is assumed to be empty, with no machine qualified for any product. The weekly demand for future production scheduling is uncertain and randomly generated from a uniform distribution in the

Table 6.3: Size of the deterministic equivalent of the S-MQO problem.

S	Constraints		Variables	
	Equality	Inequality	Continuous	Binary
1	1,680	7,328	7,140	60
5	8,400	36,640	35,700	60
10	16,800	73,280	71,400	60
20	33,600	146,560	142,800	60

experiments as shown in Table 6.2. Although in a real semiconductor back-end facility, there are at least 20-30 product families even after product aggregation. However, it turns out for either 15 or 25 products, even the deterministic equivalent formulation with 5 demand scenarios is still hard to solve to optimally within 30 hours. As a result, only the small 5-product problem is tested here to compare two solution methods of the stochastic S-MQO model. The production system description and weekly demand information for the 5-product problem are shown in Table 6.1 and Table 6.2 respectively. The available percentage of machine capacity in each time period A is set to be 80% in all cases. The WIP inventory in the system is estimated using little's law

$$I_{p,n,0} = \bar{t}_{p,n} \cdot \bar{d}_p, \ \forall p, n.$$

In the experiments, $\bar{t}_{p,n}$ is estimated by the expected processing time of product p at stage n from Table 6.1, and $\bar{d}_p$ is estimated by the expected demand of product p from Table 6.2 divided by total number of periods 84 in a week.

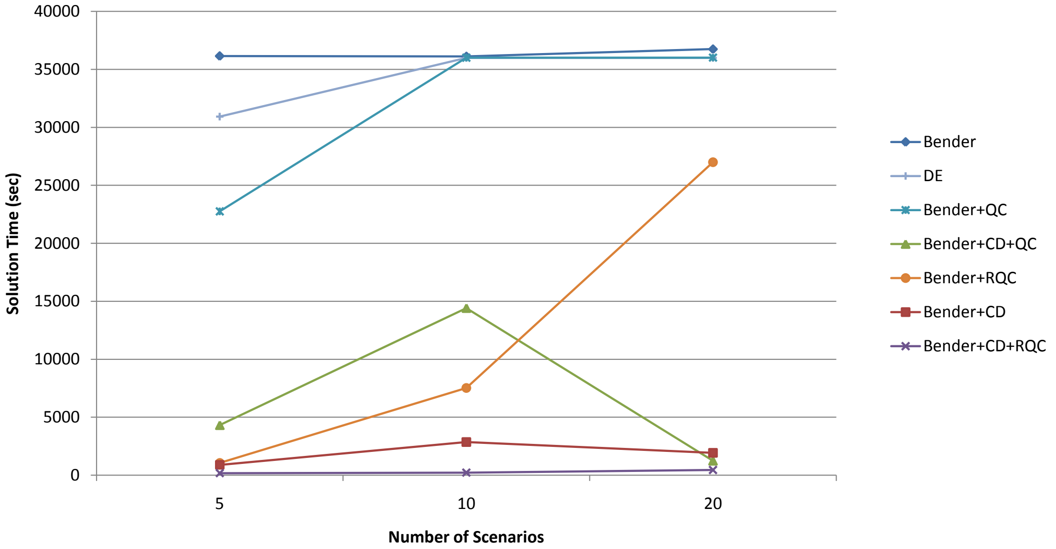
The sizes of the deterministic equivalents of the S-MQO problem for different S values are given in Table 6.3. There is a positive linear relationship between the number of constraints and continuous variables and the number of possible scenarios S. Even for a small problem instance with only 5 products and 12 machines, there are 60 binary variables in the formulation. For a typical test facility with 25 aggregated product families and 50 bottleneck-stage machines, there will be 1250 binary variables, thus making it very difficult to solve.

Performance of Different Solution Methods

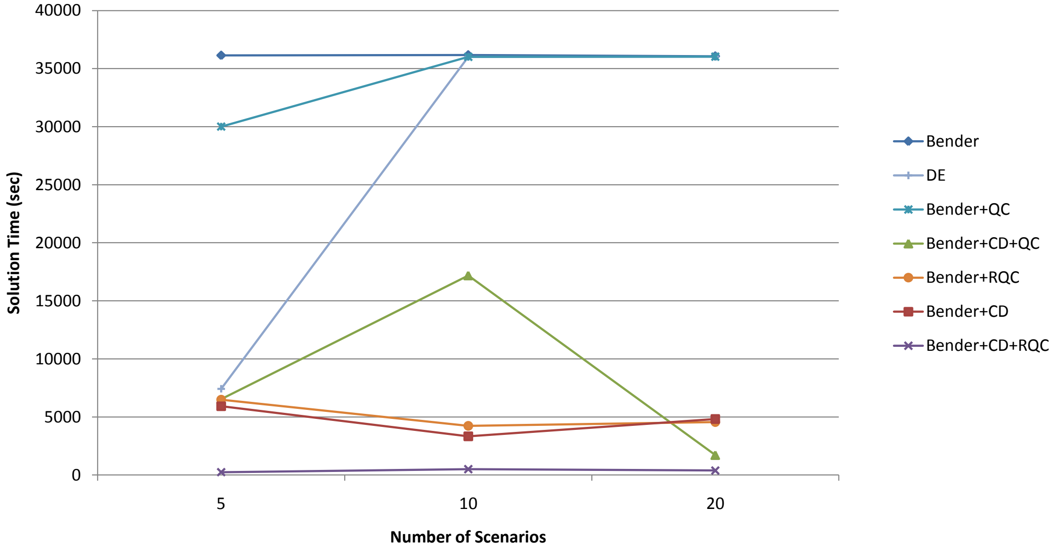
In the experiment, two different solution methods for the *S*-MQO model are tested. One is to solve the deterministic equivalent formulation (DE). The other is the L-shaped method (Bender). Proposed acceleration techniques of the L-shaped method are also tested, including cut disaggregation (CD), qualification cuts (QC), and relaxed qualification cuts (RQC). Solution times of all tested solution methods are ploted in Figure 6.2 for different *S* values and machine utilizations. More details about the solution times of different methods are shown in Table 6.4, including solution/decomposition (BD) time, time for adding qualification cuts before the decomposition (QC time), number of iterations in the decomposition algorithm, and optimality gap at the end of runtime limit (36000 sec). L-shaped method with cut disaggregation and relaxed qualification cuts ("Bender + CD + RQC") has the shortest solution times and fewest numbers of iterations. L-shaped method with cut disaggregation and qualification cuts ("Bender + CD + QC") has relatively few numbers of iterations but the unstable solution times. It is also noted that the time required for solving single-scenario qualification subproblems (QC time) increases significantly when *S* increases. As a result, adding qualification cuts is not suitable for real size problem instances. L-shaped method with cut disaggregation ("Bender + CD") has relatively short solution times but relatively large numbers of iterations, which could make it unsuitable for real size problem instances either. All other solution methods have both long solution times and larger number of iterations.

The quality of solutions of different methods are listed in Table 6.5 for different *S* values and machine utilizations. Optimal solutions obtained with the first two methods are also optimal to the original *S*-MQO model. However, optimal solutions obtained with the last four methods can be sub-optimal to the original *S*-MQO model, due to QC/RQC cuts. Both the total qualification costs and the expected total backorder costs are shown in the “Q cost” and “B cost” columns respectively in Table 6.5. In the experiment, $c_{p,n,m} = 0.1$ $(\forall\ p,n,m)$ and $b_p = 1$ $(\forall\ p)$. From “Bender + CD” to “Bender + QC” or “Bender + CD + QC”, the optimal “B cost” does not increase, and the optimal “Q cost” and “Total cost” increase slightly. For “Bender + RQC” and “Bender + CD + RQC”, the optimal “B cost”, “Q cost” and “Total cost” all increase. This is consistent with the previous analysis. The increase in “B cost” for “Bender + RQC” and “Bender + CD + RQC” is significant when S is 20. The reason is that $c_{p,n,m} < P(\xi_s)b_p$ does not hold anymore when S is 20. Therefore, $c_{p,n,m}$’s and b_p’s should be chosen carefully to make sure that $c_{p,n,m} < P(\xi_s)b_p$ is valid if “Bender + CD + QC” is to be implemented. “Bender + CD + RQC” and “Bender + CD” are recommended for large size problem instances because of short solution times and small numbers of iterations. If ”Bender + CD” does not find the optimal solution and ”Bender + CD + RQC” finds one, thus providing an upper bound of the S-MQO model, a lower bound can be estimated by the LP relaxation of the original S-MQO problem.

At the end, the optimal qualification matrices obtained using the L-shaped method with cut disaggregation for different S values and machine utilizations are evaluated using a different set of 20 demand scenarios generated according to the distributions in Table 6.2. Each demand scenarios is given an equal probability of 0.05. A production scheduling linear program is solved for each demand scenario and each optimal qualification matrix. The total qualification cost and expected total backorder cost for each optimal qualification matrix are listed in the ”Q cost” and ”B cost” columns of Table 6.6. Optimal qualification matrices from the deterministic model using the average or maximal demand are listed in the first and second row. For both 60% and 90% machine utilization cases, the optimal qualification matrices obtained from the stochastic model outperform those obtained from the deterministic model. For the stochastic model, the optimal qualification matrix obtained with more demand scenarios also has better performance, because a larger number of demand scenarios provides a better approximation of the original continuous distribution.



(a) 60% Utilization Cases



(b) 90% Utilization Cases

Figure 6.2: Solution times of different solution methods

Table 6.4: Solution time comparison of different acceleration methods .

$S = 5$	60% Utilization				90% Utilization			
	BD time	QC time	Iterations	Gap	BD time	QC time	Iterations	Gap
	(sec)	(sec)		(%)	(sec)	(sec)		(%)
Bender	36147		524	41	36143		605	11
Bender + CD	893		197	0	5919		452	0
Bender + QC	22750	3837	2494	0	30006	4960	2019	2
Bender + CD + QC	4315	3819	80	0	6534	4965	95	0
Bender + RQC	1064	3	200	0	6491	5	516	0
Bender + CD + RQC	177	3	28	0	244	4	12	0
$S = 10$	60% Utilization				90% Utilization			
	BD time	QC time	Iterations	Gap	BD time	QC time	Iterations	Gap
	(sec)	(sec)		(%)	(sec)	(sec)		(%)
Bender	36122		349	61	36168		755	17
Bender + CD	2855		183	0	3326		161	0
Bender + QC	36012	13779	1907	31	36015	16290	803	2
Bender + CD + QC	14407	13764	55	0	17176	16286	38	0
Bender + RQC	7524	4	613	0	4235	5	228	0
Bender + CD + RQC	225	6	18	0	506	6	19	0
$S = 20$	60% Utilization				90% Utilization			
	BD time	QC time	Iterations	Gap	BD time	QC time	Iterations	Gap
	(sec)	(sec)		(%)	(sec)	(sec)		(%)
Bender	36751		454	38	36067		314	67
Bender + CD	1924		126	0	4826		182	0
Bender + QC	36018	49315	1426	29	36031	26783	706	8
Bender + CD + QC	1246	50158	49	0	1719	26813	33	0
Bender + RQC	26998	4	946	0	4561	7	134	0
Bender + CD + RQC	450	4	17	0	387	6	11	0

Table 6.5: Solution quality comparison of different acceleration methods.

$S = 5$	60% Utilization				90% Utilization			
	Q cost	B cost	Total cost	Gap (%)	Q cost	B cost	Total cost	Gap (%)
Bender	2	4.2	6.2	41	4.0	17.3	21.3	11
Bender + CD	2.1	2.6	4.7	0	2.6	17.3	19.9	0
Bender + QC	2.1	2.6	4.7	0	2.5	17.7	20.2	2
Bender + CD + QC	2.1	2.6	4.7	0	2.7	17.4	20.1	0
Bender + RQC	2.3	2.5	4.8	0	2.8	17.5	20.3	0
Bender + CD + RQC	2.3	2.6	4.9	0	2.8	18.2	21.0	0
$S = 10$	60% Utilization				90% Utilization			
	Q cost	B cost	Total cost	Gap (%)	Q cost	B cost	Total cost	Gap (%)
Bender	5.8	0.9	6.7	61	4.6	12.5	17.1	17
Bender + CD	2.3	0.9	3.2	0	2.8	12.7	15.5	0
Bender + QC	3.6	0.9	4.5	31	3.0	12.6	15.6	2
Bender + CD + QC	2.3	0.9	3.2	0	2.9	12.6	15.5	0
Bender + RQC	2.4	0.9	3.3	0	3	12.7	15.7	0
Bender + CD + RQC	2.4	0.9	3.3	0	3.3	12.8	16.1	0
$S = 20$	60% Utilization				90% Utilization			
	Q cost	B cost	Total cost	Gap (%)	Q cost	B cost	Total cost	Gap (%)
Bender	3.5	0.7	4.2	38	4.5	12.4	16.9	67
Bender + CD	2.3	0.8	3.1	0	2.7	11.7	14.4	0
Bender + QC	3.2	1.1	4.3	29	3.1	11.6	14.7	8
Bender + CD + QC	2.5	0.7	3.2	0	3	11.5	14.5	0
Bender + RQC	2.4	0.8	3.2	0	3.1	17.4	20.5	0
Bender + CD + RQC	2.4	0.9	3.3	0	3.3	17.4	20.7	0

Table 6.6: Evaluation of different qualification matrices.

S	60% Utilization		90% Utilization	
	Q cost	B cost	Q cost	B cost
1 (avg)	2	8.4	2.2	17.5
1 (max)	1.7	16.3	1.9	39.4
5	2.1	5.5	2.6	16.3
10	2.3	2.8	2.8	14.9
20	2.3	2.9	2.7	14.2

6.6 Summary

In this chapter, a stochastic mixed integer linear programming model (S-MQO) is proposed to optimize product-machine qualifications for a semiconductor back-end facility. Future production scheduling in a medium term with demand uncertainty is considered. Setup times are modeled indirectly. The L-shaped method and several acceleration techniques are proposed to solve the stochastic model. In the numerical experiment, a 5-product example is used to evaluate different solution methods and their solutions.

In this research, it is assumed that product-machine qualification decisions are made and implemented now for a foreseeable future with stationary demand. The models described could be readily expanded to include time-phased qualification decisions. An interesting topic for future research will be a multi-stage stochastic model for time-phased qualification decisions.

CHAPTER 7

CONCLUSION

This research is an effort to discuss and fill the gap between theoretical flexible flow shop scheduling models and real world scheduling problems. An novel optimization model is proposed to schedule a general flexible flow shop with flexible processing routes, product family related sequence-independent setups, product-machine qualifications, and customized rules for a semiconductor back-end facility. However, since the problem itself is NP-hard and the formulation size becomes too large for real size problem instances, the model can not be solved directly for an optimal solution in a reasonable time for a real back-end facility. In order to obtain a "good" schedule in a reasonable time and also include more existing customized rules/constraints in the back-end process, a deterministic scheduling system is developed and realized. The deterministic scheduling system is able to integrate tentative production plans and schedule each lot on each individual machine subject to recourse availability and scheduling rules. Small problem instances are randomly generated, and solutions from the optimization model and the DSS are compared regarding solution time and quality (measured by total backorder costs). Based on the computational experiment results, the DSS is able to provide high quality production schedules within a short time. However, quality of the DSS solutions varies depending on the configuration of the scheduling rules used in the DSS. The DSS solutions used in the previous experiment are the best solutions among all tested configurations. Experimental design is applied to understand the behavior of the deterministic scheduling system with different configurations and provide insights about schedule rules to be used under different scenarios in the future. In conclusion, the proposed optimization model offers a novel way of modeling a flexible flow shop with more flexibility and realistic details. On the other hand, the DSS provides a framework in which more customized rules/constraints and scheduling rules can be guided by a tentative production plan. The tentative production plan provides tentative deadlines for each batch at each stage to minimize total backorder costs while local scheduling rules are used to minimize setups. Both the optimization model and the DSS can be applied to other production systems with a similar structure.

As a production system configuration parameter which has significant and long-term impact on daily production scheduling in the future, the product-machine qualification matrix is studied in more detail in this research. A stochastic optimization model is proposed to find a robust product-machine qualification matrix with minimal machine qualification costs. The L-shaped method is used to decompose and solve the deterministic equivalent iteratively. Cuts are developed to decrease the number of iterations in the solution process and the solution time. Computational results are provided to justify the necessity of the stochastic model and compare different solution methods of the stochastic model. The basic idea behind this product-machine qualification optimization model can be applied to some other qualification problems, such as employee training, machine purchase, etc.

REFERENCES

A. Agnetis, A. Pacifici, F. Rossi, M. Lucertini, S. Nicoletti, F. Nicolo, G. Oriolo, D. Pacciarelli, and E. Pesaro. Scheduling of flexible flow lines in an automobile assembly plant. *European Journal of Operational Research*, 97(2):348–362, 1997.

A. Allahverdi, CT Ng, TCE Cheng, and M.Y. Kovalyov. A survey of scheduling problems with setup times or costs. *European Journal of Operational Research*, 187(3):985–1032, 2008.

C. Andres, J.M. Albarracin, G. Tormo, E. Vicens, and J.P. Garcia-Sabater. Group technology in a hybrid flowshop environment: A case study. *European Journal of Operational Research*, 167(1):272–281, 2005.

A. Aubry, A. Rossi, M.L. Espinouse, and M. Jacomino. Minimizing setup costs for parallel multi-purpose machines under load-balancing constraint. *European Journal of Operational Research*, 187(3):1115–1125, 2008.

J.F. Benders. Partitioning procedures for solving mixed-variables programming problems. *Numerische Mathematik*, 4(1):238–252, 1962.

V. Birge François and R. John. A multicut algorithm for two-stage stochastic linear programs. *European Journal of Operational Research*, 34(3):384–392, 1988.

V. Botta-Genoulaz. Hybrid flow shop scheduling with precedence constraints and time lags to minimize maximum lateness. *International Journal of Production Economics*, 64(1-3):101–111, 2000.

K.E. Bourland and L.K. Carl. Parallel-machine scheduling with fractional operator requirements. *IIE Transactions*, 26(5):56–65, 1994.

SA Brah and JL Hunsucker. Branch and bound algorithm for the flow shop with multiple processors. *European journal of operational research*, 51(1):88–99, 1991.

K. Brockmann and W. Dangelmaier. A parallel branch bound algorithm for makespan optimal sequencing in flow shops with parallel machines. In *Proc. 2nd IMACS International Multiconference on Computational Engineering in Systems Applications*, pages 431–436, 1997.

K. Brockmann, W. Dangelmaier, and N. Holthofer. Parallel branch bound algorithm for makespan optimal scheduling in flow shops with multiple processors. In *Operations research proceedings 1997: selected papers of the Symposium on Operations Research (SOR'97), Jena, September 3-5, 1997*, page 428. Springer, 1998.

P. Brucker, B. Jurisch, and A. Krämer. Complexity of scheduling problems with multi-purpose machines. *Annals of Operations Research*, 70:57–73, 1997.

G.M. Campbell. Using short-term dedication for scheduling multiple products on parallel machines. *Production and Operations Management*, 1(3):295–307, 1992.

J. Carlier and E. Néron. An exact method for solving the multi-processor flow-shop. *RAIRO Operations Research*, 34:1–25, 2000.

T.C.E. Cheng, J.N.D. Gupta, and G. Wang. A review of flowshop scheduling research with setup times. *Production and Operations Management*, 9(3):262–282, 2000.

D.M. Chiang, R.S. Guo, and F.Y. Pai. Improved customer satisfaction with a hybrid dispatching rule in semiconductor back-end factories. *International Journal of Production Research*, 46(17):4903–4923, 2008.

G.B. Dantzig and P. Wolfe. Decomposition principle for linear programs. *Operations research*, 8(1):101–111, 1960.

S. Dauzère-Pérès and J. Paulli. An integrated approach for modeling and solving the general multiprocessor job-shop scheduling problem using tabu search. *Annals of Operations Research*, 70:281–306, 1997.

F.Y. Ding and D. Kittichartphayak. Heuristics for scheduling flexible flow lines. *Computers and Industrial Engineering*, 26(1):27–34, 1994.

A. Drexl and M. Mundschenk. Long-term staffing based on qualification profiles. *Mathematical Methods of Operations Research*, 68(1):21–47, 2008.

RL Graham. Bounds on multiprocessing timing anomalies. *SIAM Journal on Applied Mathematics*, 17(2):416–429, 1969.

AGP Guinet and MM Solomon. Scheduling hybrid flowshops to minimize maximum tardiness or maximum completion time. *International journal of production research*, 34(6):1643–1654, 1996.

J.N.D. Gupta. Two-stage, hybrid flowshop scheduling problem. *Journal of the Operational Research Society*, pages 359–364, 1988.

J.N.D. Gupta, K. Krüger, V. Lauff, F. Werner, and Y.N. Sotskov. Heuristics for hybrid flow shops with controllable processing times and assignable due dates. *Computers and Operations Research*, 29(10):1417–1439, 2002.

I. Harjunkoski and I.E. Grossmann. Decomposition techniques for multistage scheduling problems using mixed-integer and constraint programming methods. *Computers and Chemical Engineering*, 26(11):1533–1552, 2002.

W. Huang and S. Li. A two-stage hybrid flowshop with uniform machines and setup times. *Mathematical and Computer Modelling*, 27(2):27–46, 1998.

J. Hurink, B. Jurisch, and M. Thole. Tabu search for the job-shop scheduling problem with multi-purpose machines. *OR Spectrum*, 15(4):205–215, 1994.

J.P. Ignizio. Cycle time reduction via machine-to-operation qualification. *International Journal of Production Research*, 47(24):6899–6906, 2009.

S. Jarugumilli, M. Fu, N. Keng, C. DeJong, R. Askin, and J. Fowler. Framework for execution level capacity allocation decisions for assembly: test facilities using integrated optimization-simulation models. In *Proceedings of the 40th Conference on Winter Simulation*, pages 2292–2297. Winter Simulation Conference, 2008.

ZH Jin, K. Ohno, T. Ito, and SE Elmaghraby. Scheduling hybrid flowshops in printed circuit board assembly lines. *Production and Operations Management*, 11(2):216–230, 2002.

S.M. Johnson. Optimal two-and three-stage production schedules with setup times included. *Naval research logistics quarterly*, 1(1):61–68, 1954.

C. Johnzén, P. Vialletelle, S. Dauzère-Pérès, C. Yugma, and A. Derreumaux. Impact of qualification management on scheduling in semiconductor manufacturing. In *Proceedings of the 40th Conference on Winter Simulation*, pages 2059–2066, 2008.

B. Jurisch. Lower bounds for the job-shop scheduling problem on multi-purpose machines. *Discrete Applied Mathematics*, 58(2):145–156, 1995.

T. Kis and E. Pesch. A review of exact solution methods for the non-preemptive multiprocessor flowshop problem. *European Journal of Operational Research*, 164(3):592–608, 2005.

S. Kochhar and RJT Morris. Heuristic methods for flexible flow line scheduling. *Journal of Manufacturing Systems*, 6(4):299–314, 1987.

C. Koulamas and G.J. Kyparisis. Asymptotically optimal linear time algorithms for two-stage and three-stage flexible flow shops. *Naval Research Logistics*, 47(3): 259–268, 2000.

M.E. Kurz and R.G. Askin. Scheduling flexible flow lines with sequence-dependent setup times. *European Journal of Operational Research*, 159(1):66–82, 2004.

C.Y. Lee and G.L. Vairaktarakis. Minimizing makespan in hybrid flowshops. *Operations Research Letters*, 16(3):149–158, 1994. ISSN 0167-6377.

V.J. Leon and B. Ramamoorthy. An adaptable problem-space-based search method for flexible flow line scheduling. *IIE transactions*, 29(2):115–125, 1997.

H.T. Lin and C.J. Liao. A case study in a two-stage hybrid flow shop with setup time and dedicated machines. *International Journal of Production Economics*, 86(2):133–143, 2003.

J.D.C. Little. A proof of the queuing formula L=λW. *Operations Research*, 9(3): 383–387, 1961.

C.Y. Liu and S.C. Chang. Scheduling flexible flow shops with sequence-dependent setup effects. *IEEE Transactions on Robotics and Automation*, 16(4):408–419, 2000.

W. Liu, TJ Chua, TX Cai, FY Wang, and WJ Yan. Practical lot release methodology for semiconductor back-end manufacturing. *Production Planning & Control*, 16 (3):297–308, 2005.

R. Logendran, S. Carson, and E. Hanson. Group scheduling in flexible flow shops. *International Journal of Production Economics*, 96(2):143–155, 2005.

R. Logendran, P. deszoeke, and F. Barnard. Sequence-dependent group scheduling problems in flexible flow shops. *International Journal of Production Economics*, 102(1):66–86, 2006.

Y. Mati and X. Xie. The complexity of two-job shop problems with multi-purpose unrelated machines. *European Journal of Operational Research*, 152(1):159–169, 2004.

E. Mokotoff. Parallel machine scheduling problems: a survey. *Asia Pacific Journal of Operational Research*, 18(2):193–242, 2001.

E.G. Negenman. Local search algorithms for the multiprocessor flow shop scheduling problem. *European Journal of Operational Research*, 128(1):147–158, 2001.

E. Néron, P. Baptiste, and J.N.D. Gupta. Solving hybrid flow shop problem using energetic reasoning and global operations. *Omega*, 29(6):501–511, 2001.

E. Nowicki and C. Smutnicki. The flow shop with parallel machines: A tabu search approach. *European Journal of Operational Research*, 106(2-3):226–253, 1998.

S. Phadnis, J. Brevick, and S. Irani. Development of a new heuristic for scheduling flow-shops with parallel machines by prioritizing bottleneck stages. *Journal of Integrated Design and Process Science*, 7(1):87–97, 2003.

M.C. Portmann, A. Vignier, D. Dardilhac, and D. Dezalay. Branch and bound crossed with GA to solve hybrid flowshops. *European Journal of Operational Research*, 107(2):389–400, 1998.

D. Quadt and H. Kuhn. A taxonomy of flexible flow line scheduling procedures. *European Journal of Operational Research*, 178(3):686–698, 2007.

A. Rossi. A robustness measure of the configuration of multi-purpose machines. *International journal of production research*, 48(3-4):1013–1033, 2010.

R. Ruiz and C. Maroto. A genetic algorithm for hybrid flowshops with sequence dependent setup times and machine eligibility. *European Journal of Operational Research*, 169(3):781–800, 2006.

M.S. Salvador. *A solution to a special class of flow shop scheduling problems*. PhD thesis, Case Western Reserve University, 1972.

T.J. Sawik. A scheduling algorithm for flexible flow lines with limited intermediate buffers. *Applied stochastic models and data analysis*, 9(2):127–138, 1993.

A.I. Sivakumar. Optimization of a cycle time and utilization in semiconductor test manufacturing using simulation based, on-line, near-real-time scheduling system. In *Proceedings of the 31st conference on Winter simulation: Simulation—a bridge to the future-Volume 1*, pages 727–735, 1999.

A.I. Sivakumar and C.S. Chong. A simulation based analysis of cycle time distribution, and throughput in semiconductor backend manufacturing. *Computers in Industry*, 45(1):59–78, 2001.

H. Soewandi and S.E. Elmaghraby. Sequencing three-stage flexible flowshops with identical machines to minimize makespan. *IIE Transactions*, 33(11):985–994, 2001.

R. Uzsoy, LA Martin-Vega, C.Y. Lee, and PA Leonard. Production scheduling algorithms for a semiconductor test facility. *IEEE Transactions on Semiconductor Manufacturing*, 4(4):270–280, 1991.

R.M. Van Slyke and R. Wets. L-shaped linear programs with applications to optimal control and stochastic programming. *SIAM Journal on Applied Mathematics*, pages 638–663, 1969.

G. Weigert, A. Klemmt, and S. Horn. Design and validation of heuristic algorithms for simulation-based scheduling of a semiconductor Backend facility. *International Journal of Production Research*, 47(8):2165–2184, 2009.

S. Werner, S. Horn, G. Weigert, and R. Jahnig. Simulation based scheduling system in a semiconductor backend facility. In *Simulation Conference, 2006. WSC 06. Proceedings of the Winter*, pages 1741–1748, 2006.

M.C. Wu, YL Huang, YC Chang, and KF Yang. Dispatching in semiconductor fabs with machine-dedication features. *The International Journal of Advanced Manufacturing Technology*, 28(9):978–984, 2006.

M.C. Wu, H. Jiang Jr, and W.J. Chang. Scheduling a hybrid MTO/MTS semiconductor fab with machine-dedication features. *International Journal of Production Economics*, 112(1):416–426, 2008.

APPENDIX A

A MIXED INTEGER LINEAR PROGRAMMING MODEL FOR GENERALIZED FLEXIBLE FLOW SHOP SCHEDULING

Here we present a mixed integer linear programming model for scheduling generalized flexible flow shops. Similar to a flexible flow shop, a generalized flexible flow shop consists of process stages with unrelated parallel machines. Products are allowed to skip stages. In addition, more than one operation could be done at one stage. Another common and important attribute of semiconductor back-end process is also included, that is, some lower-speed chips can be substituted by higher-speed chips during the packaging steps. This feature is modeled by the substitution variables $R_{p,q,o,t}$'s and substitution indicators $\xi_{p,q,o}$'s. Delay times between stages are also modeled, which represent material moving times or throughput times at non-bottleneck stages. On the other hand, batch production constraints are relaxed. Therefore $X_{p,o,m,t}$'s, $I_{p,o,t}$'s, $B_{p,t}$'s, and $R_{p,q,o,t}$'s are defined as continuous variables. Product family related sequence-independent setups are considered. This model can be applied to the back-end process where batch production is not required.

Notation:

P: number of products, with index p

N: number of stages, with index n

$M[n]$: number of unrelated machines at stage n

O_p: number of operations in the route of product p, with index o

T: number of time periods, with index t

K: a big number, used in the formulation

C: capacity of one machine per time period, which can also be machine dependant and denoted by $C_{n,m}$

$B_{p,0}$: initial back order quantity of product family p

$I_{p,o,0}$: initial inventory of product p after operation o

b_p: unit back order cost of product p

$d_{p,t}$: demand quantity of product p at the end of time period t

$s_{p,o,m}$: set up time for product p and operation n on machine m at stage n

$t_{p,o,m}$: unit processing time of product p and operation o on machine m at stage n

$c_{p,q,o}$: unit substitution cost for using product p as q at operation o

$q_{p,n,m}$: product-machine qualification indicator, 1 if machine m at stage n is qualified for product p and 0 otherwise

$stage[o]$: stage index for operation o

$\xi_{p,q,o}$: binary substitution indicator, 1 if product p can be used as product q at operation o and 0 otherwise

$delay_{p,o}$: delay time between operation o and the next operation in the route for product p

Continuous Variables:

$X_{p,o,m,t}$: production quantity of product p and operation o in time period t on machine m at stage $stage[o]$

$I_{p,o,t}$: inventory quantity of product p at the end of time period t after operation o

$B_{p,t}$: back order quantity of the product p at the end of time period t

$R_{p,q,o,t}$: quantity of product q substituted by product p at operation o in time t

$W^1_{p,o,m,t}$: time spent in time period t on the setup that ends in time period t for product p and operation o on machine m at stage $stage[o]$

$W^2_{p,o,m,t}$: time spent in time period t on the setup that continues in time period $t+1$ for product p and operation o on machine m at stage $stage[o]$

$L_{p,o,m,t}$: cumulative time by the end of time period t spent on the setup that continues to time period $t+1$ for product p and operation o on machine m at stage $stage[o]$

Binary Variables:

$Y_{p,o,m,t}$: 1 if a setup for product p and operation o on machine m at stage $stage[o]$ ends in period t; 0 otherwise

$Z_{p,o,m,t}$: 1 if product p and operation o can be processed on machine m at the beginning of time period $t+1$ without a setup; 0 otherwise

$U_{p,o,m,t}$: 1 if a setup for product p and operation o is going on at the end of the period t and will continue at the beginning of period $t+1$ on machine m at stage $stage[o]$; 0 otherwise

$$min \sum_{p,t} b_p B_{p,t} + \sum_{p,q,o,t} c_{p,q,o} R_{p,q,o,t} \tag{A.1}$$

$$s.t.\ I_{p,o,t-1} + \sum_m X_{p,o,m,t} - \sum_m X_{p,o+1,m,t+delay_{p,o}} + \sum_q \xi_{q,p,o} R_{q,p,o,t}$$

$$- \sum_q \xi_{p,q,o} R_{p,q,o,t} = I_{p,o,t},\ \forall\ p, o < O_p, t \tag{A.2}$$

$$I_{p,O_p,t-1} - B_{p,t-1} + \sum_m X_{p,O_p,m,t} + \sum_q \xi_{q,p,O_p} R_{q,p,O_p,t} - d_{p,t+delay_{p,o}}$$

$$- \sum_q \xi_{p,q,O_p} R_{p,q,O_p,t} = I_{p,O_p,t} - B_{p,t},\ \forall\ p, t \tag{A.3}$$

$$\sum_m X_{p,o+1,m,t+delay_{p,o}} \leq I_{p,o,t-1},\ \forall\ p, o \geq 2, t \tag{A.4}$$

$$R_{p,q,o,t} \leq K \xi_{p,q,o},\ \forall\ p, q \neq p, o, t \tag{A.5}$$

$$\sum_{p,o:stage[o]=n} t_{p,o,m} X_{p,o,m,t} + \sum_{p,o:stage[o]=n} (W^1_{p,o,m,t} + W^2_{p,o,m,t}) \leq C,$$

$$\forall\ n, 1 \leq m \leq M[n], t \tag{A.6}$$

$$X_{p,o,m,t} \leq K(Z_{p,o,m,t-1} + Y_{p,o,m,t}),\ \forall\ p, o, m, t \tag{A.7}$$

$$W^1_{p,o,m,t} \leq C Y_{p,o,m,t},\ \forall\ p, o, m, t \tag{A.8}$$

$$W^2_{p,o,m,t} \leq C U_{p,o,m,t},\ \forall\ p, o, m, t \tag{A.9}$$

$$\sum_{p,o:stage[o]=n} (Z_{p,o,m,t} + U_{p,o,m,t}) = 1,\ \forall\ n, 1 \leq m \leq M[n], t \tag{A.10}$$

$$Z_{p,o,m,t} \leq 1 + Y_{p,o,m,t} - Y_{q,o,m,t},\ \forall\ p \neq q, o, m, t \tag{A.11}$$

$$Z_{p,o,m,t} \leq Z_{p,o,m,t-1} + Y_{p,o,m,t},\ \forall\ p, o, m, t \tag{A.12}$$

$$s_{p,o,m} Y_{p,o,m,t} \leq L_{p,o,m,t-1} + W^1_{p,o,m,t},\ \forall\ p, o, m, t \tag{A.13}$$

$$L_{p,o,m,t} \leq s_{p,o,m} U_{p,o,m,t},\ \forall\ p, o, m, t \tag{A.14}$$

$$L_{p,o,m,t} - W^2_{p,o,m,t} \leq L_{p,o,m,t-1},\ \forall\ p, o, m, t \tag{A.15}$$

$$L_{p,o,m,t} - W^2_{p,o,m,t} \leq s_{p,o,m}(1 - Y_{q,o,m,t}),\ \forall\ p, o, m, t \tag{A.16}$$

The objective (A.1) is to minimize the summation of total backorder costs and total substitution costs. Constraints (A.2) are the inventory balance constraints for each product at each operation except for the last in each time period. Each inventory balance constraint states that the ending inventory quantity in period t is equal to the starting inventory quantity plus production quantity minus consumption quantity at next operation in the route of this product in a future period. Since the delay time between the current operation o and the next operation in the route is $delay_{p,o}$, consumption quantity at the next operation in period $t + delay_{p,o}$ has to be put into transit and thus removed from the inventory pile after operation o in current period t. In addition, quantity of product p substituted by any other product q and quantity of any other product q substituted by product p are also considered. Constraints (A.3) are the inventory balance constraints for each product at last operation in each time period, and instead of the consumption quantity at the next operation backorder quantity and demand quantity are considered. Constraints (A.4) state that production quantity at operation $o+1$ in period $t + delay_{p,o}$ has to be less than the available starting inventory at previous operation o in period t. Constraints (A.5) are the substitution constraints, indicating whether one product can be substituted by another product. Constraints (A.6) are the capacity constraints for each machine in each time period, stating that the total production and setup times over all products and operations at one machine can not exceed the available capacity of the machine in that time period. Constraints (A.7) state that processing of product p for operation o can not be done on machine m unless the setup is carried over from the previous time period ($Z_{p,o,m,t-1} = 1$) or finished in current time period ($Y_{p,o,m,t}$=1). Constraints (A.8) and Constraints (A.9) are constraints about setup time decision variables $W^1_{p,o,m,t}$ and $W^2_{p,o,m,t}$ based on their definitions. Constraints (A.10) state that at the end of any time period, the machine is either being setup or producing. Constraints (A.11) states that if there is a setup completed for product q in time period t and a setup status for product p is carried over to the next time period $t+1$, there has to be a setup completed for product p after product q is processed in current time period t. Constraints (A.12) state that if a setup for product p is carried over to the next time period $t+1$ ($Z_{p,o,m,t} = 1$), there has to be either a setup for product p completed in time period t ($Y_{p,o,m,t} = 1$) or a setup for product p carried over from previous time period $t-1$ ($Z_{p,n,m,t-1} = 1$). Constraints (A.13) state that if a setup for product p and operation o on machine m is finished in period t, the cumulative time spent on this setup, that is $L_{p,o,m,t-1} + W^1_{p,o,m,t}$, should be greater than or equal to the required setup time $s_{p,o,m}$. Constraints (A.14) are based on the definition of $L_{p,o,m,t}$'s, stating that the cumulative setup time to be carried over to the next period t, that is $L_{p,o,m,t}$, is set to zero unless the setup is continuing in the next period $t+1$. Constraints (A.15) and (A.16) together state that if there is a setup completed for another product q in current time period t, the cumulative setup time carried over to next time period for product t is set to $W^2_{p,o,m,t}$; otherwise, the cumulative setup time carried over to next time period for product p is equal to $W^2_{p,o,m,t} + L_{p,o,m,t-1}$. Constraints (A.10-A.16) are used to model the condition when one setup lasts over more than two time periods.

APPENDIX B

FUNCTIONS DEFINED IN SCHEDULER

The scheduler is based on a discrete event simulation structure, which means it models every event and the status of every resource or constraint in the system. The event types and functions defined in the scheduler are described in more details here. There are six types of events defined in the scheduler: lot arrival to a stage (*arrival*), lot departure from a machine (*departure*), end of a setup (*end_setup*), end of a preventive maintenance (*end_pm*), end of a machine downtime (*end_down*), check and schedule of all idle machines at the beginning of every 2-hr time period (*check_time_point*). When an event occurs, the status of a machine or a staff will change. As a result, the system status will be updated according to the event type, as shown in Algorithm 4. When a lot arrives at a stage, either machine from the stage is chosen to process this lot or the lot is put in the queue, as shown in Algorithm 5. In the scheduler, whenever before a idle qualified machine is setup for a product, we will first check whether there is an available staff to perform the setup operation, whether the number of machines already setup for the product at this stage is less than the maximal number of machines allowed to be setup for this product at this stage, as well as whether the setup and production of this lot will conflict any scheduled preventive maintenance or downtime of the machine. This check is performed in line 3 of Algorithm 5. When a machine finishes processing a lot, Algorithm 6 is used to schedule an arrival event to the next operation and Algorithm 11 is then called to choose a job/lot from the queue for the machine. When a setup, preventive maintenance, or machine downtime ends, the status of a staff will change from busy to idle, and thus Algorithm 11 is then called to choose a lot from the queue for the machine, as shown in Algorithm 6, 8, 9, or 10. At the beginning of a 2-hr time period, the status of all lots in the queue will change because we define the priority of a lot by the product priority as well as comparison of the production time period of the lot in the plan to current time period. If the production time period of a lot in the plan is earlier than the current time period, the lot is defined as a late lot that has a higher priority. Otherwise the lot is defined as an early lot that has a lower priority. So at the beginning of every 2-hr time period, Algorithm 11 will be called to choose a lot from the queue for any idle machine at any stage.

Algorithm 4 *main*() Function

```
while $event\_list \neq empty \parallel current\_time \neq planning\_horizon$ do
    find $next\_event$ with earliest $event\_time$ in the $event\_list$
    if $next\_event.type = arrival$ then
        run $arrive()$
    else if $next\_event.type = departure$ then
        run $depart()$
    else if $next\_event.type = check\_time\_point$ then
        run $check\_time\_point()$
    else if $next\_event.type = end\_setup$ then
        run $end\_setup()$
    else if $next\_event.type = end\_pm$ then
        run $end\_pm()$
    else if $next\_event.type = end\_down$ then
        run $end\_down()$
    end if
end while
```

Algorithm 5 *arrive*() Function

```
if there is at least one qualified idle machine then
    choose a machine with smallest setup time
    if a setup is needed for the chosen machine then
        if a setup can be performed for this product then
            change the status of the machine to being setup
            change the status of the worker to busy
            schedule an $end\_setup$ event
            schedule a $departure$ event
        else
            put the job in the queue
        end if
    else
        change the status of the machine to being producing
        schedule a $departure$ event from the machine
    end if
else
    put the job in the queue
end if
```

Algorithm 6 *depart*() Function

```
if current stage is not the last stage for current product then
    schedule an arrival event to the next stage in the route
end if
run search_queue() to choose a job from the queue for the idle machine
```

Algorithm 7 *check_time_point*() Function

```
for all idle machine at each stage do
    run search_queue() to choose a job from the queue for the machine
end for
```

Algorithm 8 *end_setup*() Function

```
set the machine being producing the job it is setup for
for all idle machine at each stage do
    run search_queue() to choose a job from the queue for the machine
end for
```

Algorithm 9 *end_pm*() Function

```
for all idle machine at each stage do
    run search_queue() to choose a job from the queue for current machine
end for
```

Algorithm 10 *end_down*() Function

```
for all idle machine at each stage do
    run search_queue() to choose a job from the queue for current machine
end for
```

Algorithm 11 *search_queue*() Function

```
search the queue in front of the stage for the best eligible job based on qualification matrix, setup time length, product priority, and production time period of the lot in the plan
if there is no eligible job then
    if there is a eligible job that can not be scheduled on the machine because of conflicting a scheduled preventive maintenance/downtime then
        change the status of the machine from idle to preventive maintenance/down
        schedule the $pm/downtime\_end$ event
    else
        leave the machine idle
    end if
else if the best eligible job is an early job then
    if there is an eligible late job that can not be scheduled on the machine because of conflicting a scheduled preventive maintenance then
        change the status of the machine from idle to preventive maintenance
        schedule a $pm\_end$ event
    else
        change the status of the machine from idle to be producing
        schedule a $departure$
    end if
else if the best eligible job is an late job then
    schedule the late eligible job
end if
```