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ROBUSTNESS ANALYSIS OF AN MIP FOR PRODUCTION AREAS WITH TIME CONSTRAINTS AND TOOL INTERRUPTIONS IN SEMICONDUCTOR MANUFACTURING

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ABSTRACT

This research is motivated by the need to verify and implement a schedule in a real production environment, especially in precarious production environments. This paper presents a mixed integer program (MIP) with time constraints and analysis risk parameters for tool interruptions. With the assistance of the survival analysis, a safety value will be computed and included in the MIP to downscale the available capacity. To verify the quality and robustness of the MIP, it is necessary to simulate tool interruptions and to change assumed release dates of production-bound jobs which have different stochastic distributions. To simulate these instabilities a hybrid model has been created which combines a discrete event simulation with a MIP solver. Finally, the results of the various simulations are compared.

1 INTRODUCTION

Production areas with time constraints between consecutive process steps, known as timelink areas, are tough to schedule. This is especially true in semiconductor manufacturing, which has very complex production environments with a wide variety of different process steps, multiple products and routes, jobs with varying priorities, dependencies between products and processes and fluctuating release dates for jobs and unplanned tool interruptions. The ongoing shrinkage of chip size coupled with an increased wafer density, has resulted in greater attention being paid to production areas with time constraints, due to unwanted processes like oxidation or particles that have a higher yield impact due to smaller feature sizes. Jobs with violation of time constraints often need to be scrapped, or result in costly rework. For this reason its necessary to investigate the robustness of calculated schedules that consider time constraints and tool capacity.

Many works treat the topic of scheduling formulations, such as Brucker (2007), Graham et al. (1979), Garey et al. (1976) and Jaehn and Pesch (2014), which summarize and survey deterministic scheduling formulations and characteristics for different objective functions. However, only a few papers address scheduling with time constraints between consecutive process steps in semiconductor manufacturing. Different types of time constraints are analyzed by Klemmt and Mönch (2012) who present a MIP model

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for flow shop scheduling problems with time constraints. Klemmt (2012) presents detailed formulations for numerous problem descriptions in wafer fabs. Yu et al. (2013), present a two-stage lot scheduling MIP approach with time constraints for small problems and a efficient solution procedure for larger problems. This procedure decompose the jobs in two subsets, whereby only one subset of jobs is scheduled by the MIP and the other one scheduled with dispatching. Cho et al. (2014), presented and compared two MIP formulations with the objective to determine the best gate-keeping decisions. Gate-keeping decisions from an MIP decide when a job is allowed to enter a timelink area. The MIP formulations of time constraints presented in Cho et al. (2014) were not subjected to strict conditions. They were based on a reward and sanction system. The advantage of this approach is that these MIPs are always solvable, and the generated schedules seem to be more robust with regards to time violations. On the other hand, the computation time needed to find good solutions was enormous. Approaches for robust scheduling due to uncertainties are a matter of particular interest. For example Mehta and Uzsoy (1998) and Li et al. (2011) presents classification and modeling approaches to uncertainties like a stochastic modeling based on probability theory. In this approach random events are characterized by statistical probability distributions. These researches presents also a collection of several works which use the exponential distribution or a uniform distribution to characterize the time between breakdowns of tools. Furthermore, stochastic models in reliability and survival analysis are given for example by Liu (2012), Wienke (2010) and Aven and Jensen (2013). Nevertheless, there are no detailed investigations of the robustness of schedules, with regard to time violations.

2 PROBLEM DESCRIPTION

In this section, the problem of scheduling with time constraints is described. There is a set of jobs $J := \{J_1, \dots, J_n\}$, $n \in \mathbb{N}$ that has to be scheduled. Each job $j \in J$ can have different weights $\omega_j \in \mathbb{N}$. Also each job $j \in J$ is assigned to a product $f(\cdot) : J \to R$ and each product has its own route $R := \{R_1, \dots, R_r\}$, $r \in \mathbb{N}$, $r \leq n$. For each route $i \in R$ there exist $n_i \in \mathbb{N}$ operations $O_i := \{O_{i,1}, \dots, O_{i,n_i}\}$. Furthermore there is a set of available tools $M := \{M_1, \dots, M_m\}$, $m \in \mathbb{N}$. Each tool is a single-tool, which means that only one job can be performed at any given time on a given tool. In this problem, $g \in \mathbb{N}$, $g \leq m$ has distinct processes $P := \{P_1, \dots, P_g\}$ and each process $k \in P$ has its own work center $W_k \subseteq M$, $W_k \neq \emptyset$, $\dot{\bigcup}_{k \in P} W_k = M$ with $m_k = |W_k|$ identical parallel tools. Also each tool has its own load port. Furthermore, each operation $O_{i,o}$ is associated with exactly one process $g(i,o) : O_i \to P$, which must be performed on one tool l in the associated work center $l \in W_{g(i,o)}$. It is assumed that each processing time $p_{i,o}$ for each job for a given product $i \in R$ is identical for all tools in a work center $W_{g(i,o)}$. Each job $j \in J$ receives a release date r_j, which means that it can be scheduled at any point in the future, after the release date. Similarly each tool $l \in M$ receives a release date u_l, which means that a job can only be scheduled on the given tool, if it is available. For some routes $i \in R$ there exists time constraints $t_{(i,o,q)} > 0$ between defined consecutive operations $o, q \in O_i$, $q = o + 1$, which can be formulated as

$$s_{j,q} \leq s_{j,o} + p_{i,o} + t_{(i,o,q)} \qquad j \in J, i = f(j), \tag{1}$$

where $s_{j,o}$ is the scheduled start time of job j at operation o. To restrict the flow, there is a gate in front of each timelink area. An example of a simple timelink in a production area with two different products, where only the first product has a time constraint between consecutive process steps, is shown in Figure 1.

In relation to the SEMI E10 standard, six basic equipment states were established. These six equipment states are assigned to basic up or down conditions for the survival analysis, without consideration of the Non-Scheduled Time. The results are shown in Figure 2.

In actuality, delays or inconsistencies influence the release dates of jobs. These fluctuations are generated with random numbers from three different distributions, plus an additional simulation, in order to analyze the influences on the schedule.

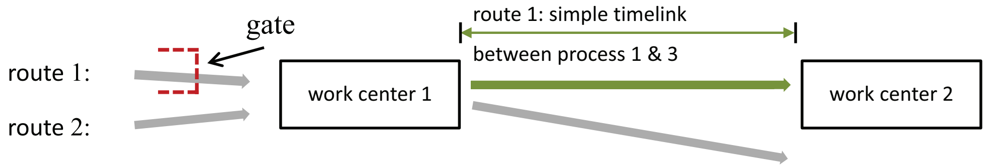


Figure 1: Simplified example of an possible timelink area.

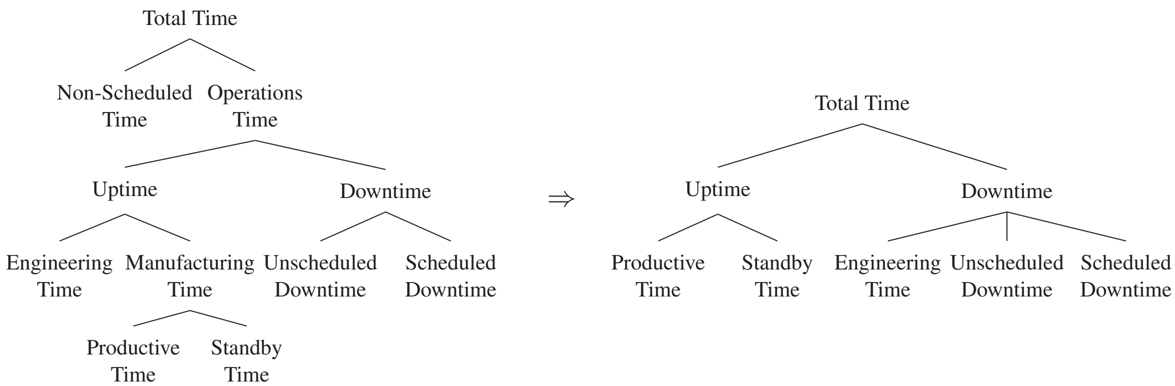


Figure 2: SEMI E10 tool state assignments necessary to survival analysis.

3 MODEL FORMULATION

The following notations are used for the model formulation:

n	$\in \mathbb{N}$	number of jobs
m	$\in \mathbb{N}$	number of tools
M	$:= \{M_1, \ldots, M_m\}$	set of tools
J	$:= \{J_1, \ldots, J_n\}$	set of jobs
R	$:= \{R_1, \ldots, R_r\}$	number of routes
P	$:= \{P_1, \ldots, P_g\}$	set of processes
O_i	$:= \{O_{i,1}, \ldots, O_{i,n_i}\}$	set of operations of route $i \in R$
$O_{i,o}$	$\in O_i$	o-th operation of route $i \in R$
$f(j)$	$: J \to R$	route from job j
$g(i,o)$	$: O_i \to P$	process $O_{i,o}$ for $i \in R$
W_k	$\subseteq M$	work center for process $k = g(i,o)$
$M_{k,l}$	$\in W_k$	l-th tool at work center W_k for $k = g(i,o)$
$p_{i,o}$	$\in \mathbb{R}_+$	process time at operation $O_{i,o}$
r_j	$\in \mathbb{R}_+$	release date of job j
u_l	$\in \overline{\mathbb{R}}_+$	tool release date ($l \in M$)
T	$:= \{(i,o,q) \mid 1 \leq o < q \leq n_i,\ i \in R\}$	set of timelink areas
T^j	$:= \{(j,o) \mid \exists q \in O_{f(j)} : o < q \wedge (f(j),o,q) \in T\}$	set of entry operations in timelink area of job j
$t_{(j,o)}$	$\in \mathbb{R}_+,\ (j,o) \in T^j$	enter time of job j at the first operation o in a timelink area
$t_{(i,o,q)}$	$\in \mathbb{R}_+,\ (i,o,q) \in T$	timelink between operation $O_{i,o}$ and operation $O_{i,q}$, $i \in R$
ω_j	$\in \mathbb{N}$	weight of job j
K	$\in \mathbb{R}_+$	a large positive number

3.1 Survival Analysis and Time Constraints

The results from the survival analysis are integrated in the time constraint formulation of the MIP. This integration downscales the capacity to minimize time violations based on tool interruptions. The time constraint formulation is similar to Maleck and Eckert (2017) and contains fundamental theory from Wienke (2010) and Liu (2012).

For reactive scheduling, it is necessary that all jobs, in a timelink area fulfill the time constraint (1), and all jobs in front of a timelink area must fulfill a tougher time constraint to minimize actual time violations due to uncertainties because of tool interruptions. The tougher time constraint is calculated with the help of safety parameters.

The up or down state of a tool $l \in M$ at time t is represented by a binary variable

$$Z_l(t) := \begin{cases} 1 & \text{, if the tool is up} \\ 0 & \text{, down.} \end{cases} \tag{2}$$

Furthermore the failure behavior of tools is predicted by a hazard rate $\lambda_T(t)$ at time t which is calculated using the quotient of the probability life density function $f_T(t)$ and the probability of survival $R_T(t) := 1 - F_T(t)$

$$\lambda_T(t) = \frac{f_T(t)}{R_T(t)}, \tag{3}$$

where T is a single random variable that is continuous and non-negative, which represents the lifetime of a tool and F_T is the associated distribution function. For basic details, see Wienke (2010) or Liu (2012).

The hazard rate $\lambda_T(t)$ for tools can be described by the classical bathtub curve, which is illustrated in Figure 3. It has three different stages.

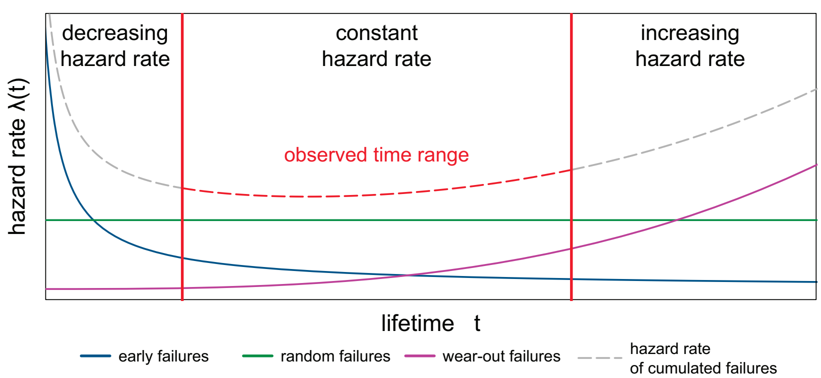


Figure 3: The three stages of the classical bathtub curve against time.

Normally, a tool for production material is in the second stage. This is due to tool qualifications in the first stage and preventative maintenance on tools in the third stage. Figure 3 illustrates that the second stage underlies a nearly constant hazard rate $\lambda_T(t) = \lambda_T(t + \Delta t)$. These specific conditions are satisfied by the exponential distribution

$$F^{exp}(t) = 1 - e^{-\lambda t}, \qquad t \geq 0. \tag{4}$$

According to the property of the exponential distribution. The hazard rate stays constant, no matter how long a tool is up, in addition, because of the Markov property the exponential distribution is memoryless. Therefore, the conditional survival probability, which is the probability that a tool will not go down within the interval $[t_0, t_0 + t]$, $t > 0$, can be formulated as

$$R_T^{exp}(t|t_0) := \mathbb{P}[T > t_0 + t | T > t_0] = \frac{e^{-\lambda(t_0+t)}}{e^{-\lambda t_0}} = e^{-\lambda t} \,. \tag{5}$$

If in a production area a tool is up at time t_0 ($Z(t_0) = 1$), F_T is exponentially distributed, and at time t_0 the tool l has a current uptime $t_{up}(l) \geq 0$, then the assumed availability of a tool for time period t is

$$\nu_l(t + t_{up}(l), t_{up}(l)) := R_T^{exp}(t + t_{up}(l)|t_{up}(l)) = e^{-\lambda(t+t_{up}(l))}. \tag{6}$$

The availability factor κ_k of a work center W_k is defined as

$$\kappa_k := \frac{1}{|W_k|} \cdot \sum_{l \in W_k} \nu_l \ , \tag{7}$$

where ν_l is the computed availability (6) of a tool $l \in M$. The time constraint of capacity $t^{\kappa}_{(i,o,q)}$ with $(i,o,q) \in T$ and $k = g(i,q)$ for all jobs in front of a timelink area is

$$t^{\kappa}_{(i,o,q)} := \kappa_k \cdot t_{(i,o,q)} \qquad \forall (i,o,q) \in T,\ k = g(i,q)\ . \tag{8}$$

It concludes that each job in front of a timelink area must satisfy

$$s_{j,q} \leq s_{j,o} + p_{i,o} + t^{\kappa}_{(i,o,q)} \qquad j \in J,\ i = f(j). \tag{9}$$

In a non-empty start system for all jobs currently in a timelink, the constraint (9) should be set to the time constraint (1). All jobs j in a timelink area that can theoretically perform the constraint (1) are summarized in J^T.

3.2 MIP Formulation

This MIP has four types of decision variables:

C_j	$\in \mathbb{R}_+$	completion time of job $j \in J$
$w_{j,o,l}$	$\in \{0,1\}$	assignment from job $j \in J$ at operation o to tool $l \in W_k$, $i = f(j)$, $k = g(i,o)$
$s_{j,o}$	$\in \mathbb{R}_+ \cup \{\infty\}$	starting time of job $j \in J$ at operation $O_{i,o}$, $i = f(j)$
$x_{h,j,o}$	$\in \{0,1\}$	1 if job $h \in J$ is scheduled before $j \in J$ at operation o, otherwise 0

The observed objective function is

$$z = \sum_{j \in J} \omega_j C_j \ \rightarrow \ min \tag{10}$$

subject to:

$$r_j \leq s_{j,1} \qquad \forall j \in J \tag{11}$$

$$s_{j,o} + p_{i,o} \leq s_{j,o+1} \qquad \forall j \in J,\ \forall o \in O_i \backslash \{O_{i,n_i}\},\ i = f(j) \tag{12}$$

$$s_{j,o} + p_{i,o} \leq C_j \qquad \forall j \in J,\ \forall o \in O_i,\ i = f(j) \tag{13}$$

$$\sum_{l \in W_k} w_{j,o,l} = 1 \qquad \forall j \in J,\ \forall o \in O_i,\ i = f(j),\ k = g(i,o) \tag{14}$$

$$w_{j,o,l} \cdot u_l \leq s_{j,o} \qquad \forall j \in J,\ \forall o \in O_i,\ \forall l \in W_{g(i,o)},\ i = f(j) \tag{15}$$

$$s_{j,q} \leq s_{j,o} + p_{i,o} + t^{\kappa}_{(i,o,q)} \qquad \forall j \in J,\ (f(j),o,q) \in T,\ (i,o) \notin T^j,\ k = g(f(j),q) \tag{16}$$

$$s_{j,q} \leq t_{j,o} + p_{i,o} + t_{(i,o,q)} \qquad \forall j \in J^T,\ i = f(j),\ (i,o,q) \in T,\ (i,o) \in T^j \tag{17}$$

$$K(w_{h,o,l} - x_{h,j,o} - 1) + s_{j,o} + p_{f(j),o} \cdot w_{j,o,l} \leq s_{h,o} \qquad \forall l \in W_{g(f(h),o)} \cap W_{g(f(j),o)}, \forall o \in O_{f(h)} \cap O_{f(j)} \tag{18}$$

$$K(w_{j,o,l} + x_{h,j,o} - 2) + s_{h,o} + p_{f(h),o} \cdot w_{h,o,l} \leq s_{j,o} \qquad \forall l \in W_{g(f(h),o)} \cap W_{g(f(j),o)}, \forall o \in O_{f(h)} \cap O_{f(j)} \tag{19}$$

Constraints (11) and (12) ensure that each job is scheduled after its release date, and with consideration to the sequence of the process steps of its route. Constraint (13) restricts the objective function (10). Equation (14) ensures that each operation is executed exactly once by a given job. The availability of tools is ensured by constraint (15). Inequalities (18) and (19) assure that only one job can be scheduled on a given tool at a given time. Constraint (16) and (17) represent the time constraints between consecutive process steps. In conjunction with J^T it is ensured that the observed problem is solvable.

3.3 Hybrid-Model Formulation

To test the robustness of the generated schedules a hybrid model with reactive scheduling was created which is shown in Figure 4. It contains a discrete event simulation (DES), which is realized through the *simcron MODELLER*, representing the production line, and a mathematical solver (IBM ILOG CPLEX) that creates the schedules with MIP. A schedule is computed hourly or if a tool interruption occurs. All jobs that are currently, or in the next hour, in front of the observed area, or in it, are used as input for the scheduler. In addition, all tools that are currently available ($Z_l(t_0) = 1, l \in M$), or assumed to be available during the next hour ($Z_l(t_0) = 0 \wedge u_l \in (t_0, t_0 + 1h]$), are scheduled. Furthermore, the MIP gets the time constraint of capacity $t^{\kappa}_{(i,o,q)}$ from (8) as input. For this problem, only the due dates for the first operations are carried over for the area. This means that the MIP schedule gives a gate decision in front of a timelink area. Further process steps of a job are scheduled by dispatching rules using the first in - first out principle (FIFO).

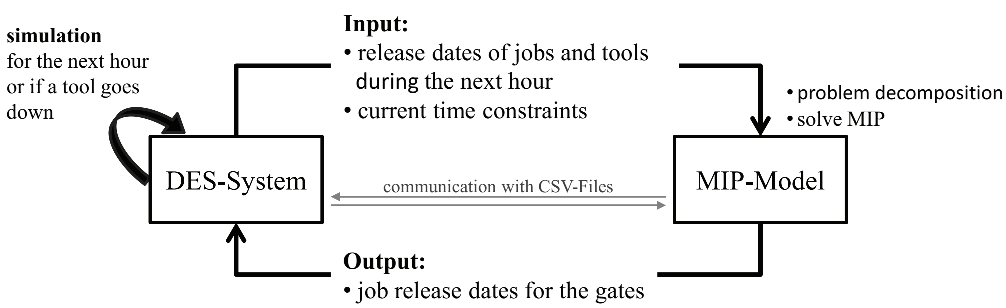


Figure 4: Illustration of the hybrid model.

Due to the complexity of the MIP a preprocessing was integrated, which states that only a defined number of jobs will be scheduled. These fulfill the maximum production capacity in the observed area in 1.25 hours. The jobs are, therefore, ordered by priority.

3.4 Robustness Analysis

The objective of the robustness analysis is to verify a schedule for practical use and investigate flow effects. This robustness analysis deals with uncertain release dates of jobs and tools after interruptions. This is done by modifying the assumed release dates during the next time range with the help of three different stochastic distributions. An example is shown in Figure 5.

First, the job release dates and tool release dates are modified by the normal distribution. Then, the normal, uniform, and log-normal distribution are used to test the robustness of the schedules by making modifications to the job and tool release dates. To test this, after a schedule is computed, all release dates during the next time range are modified, depending on the assumed release date t ($t > t_0$). This is done through a random value dependency of its distribution. The expectation is that the assumed release date and the deviation is $\Delta = 0.2 \cdot (t - t_0)$. The density functions with differing expected release dates of the three distributions are illustrated in Figure 6.

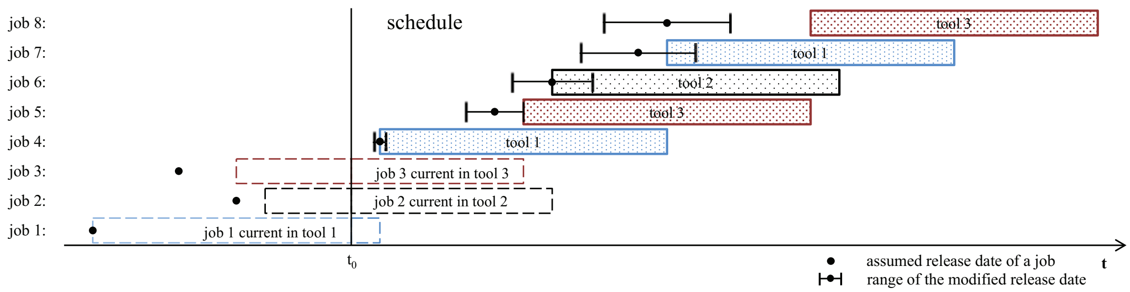


Figure 5: Illustration of a job schedule.

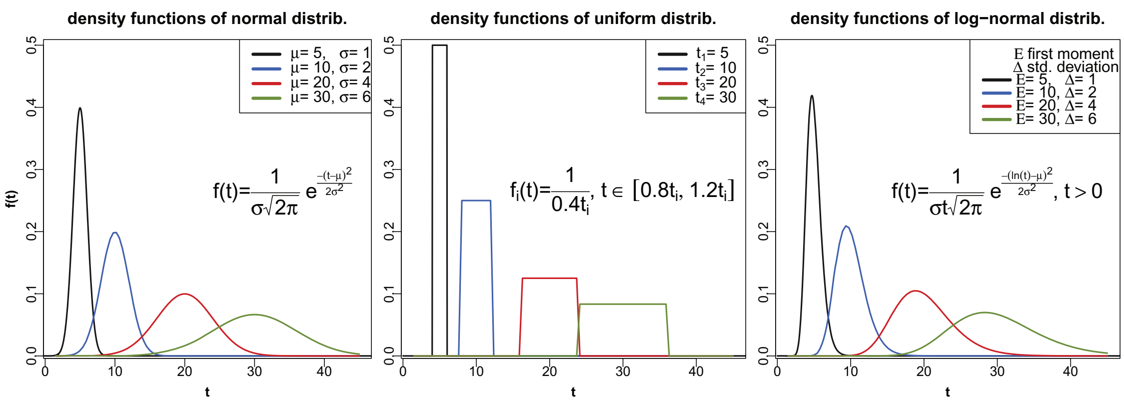


Figure 6: Illustration of density functions.

4 RESULTS ON EXAMPLE MODELS

4.1 Data Generation and Examples

The investigated production areas were generated artificially, and the used data were generated from the specific distributions. For the simulation of a more realistic production flow, the expected job release dates and expected Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR) with the assumed deviation are needed. The first observed production area is a simple flow with one timelink, as shown in Figure 1. The second example, shown in Figure 7, is more complex. It contains four different products, two of which have different time constraints, and all of which enter the same work center at the end of the observed production area. The specifications of the first example are shown in Tables 1 and 2. The specifications of the second example are shown in Tables 3 and 4, with $\mathbb{E}$ as the expected value and $\mathbb{D}$ as the associated deviation.

Table 1: Tool specifications from the first example.

process k	$\|W_k\|$	load-port capacity	**MTBF** distrib	**MTBF** $\mathbb{E}$	**MTBF** $\mathbb{D}$
P_1	3	2	Exp	60.67 h	-
P_2	4	-	Exp	40.0 h	-
process k			**MTTR** distrib	**MTTR** $\mathbb{E}$	**MTTR** $\mathbb{D}$
P_1			log-norm	7.5 h	11.25 h
P_2			log-norm	10 h	15.0 h

Table 2: Flow specifications from the first example.

	$\mathbf{R_1}$	$\mathbf{R_2}$
$o=1$: process	$g(R_1,1)=P_1, W_{P_1}$	$g(R_2,1)=P_1, W_{P_1}$
$o=1$: $p_{j,1}$	15 min/job	15 min/job
$o=2$: process	$g(R_1,2)=P_2, W_{P_2}$	-
$o=2$: $p_{j,2}$	52.5 min/job	-
job distrib	Exp	Exp
r_j	$\mathbb{E}=19$ min	$\mathbb{E}=12$ min
weight ω_j	2	1
timelink T	$\{(R_1,1,2)\}$	-
time condition	$t_{(R_1,1,2)}=4$ h	-

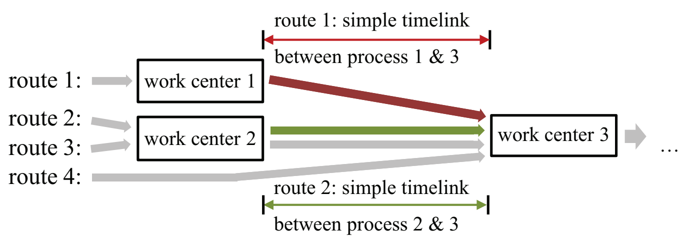


Figure 7: Second example area.

Table 3: Tool specifications from the second example.

process k	$\|W_k\|$	load-port capacity	**MTBF** distrib	**MTBF** $\mathbb{E}$	**MTBF** $\mathbb{D}$
P_1	5	2	Exp	9.75 h	-
P_2	2	2	Exp	8.66 h	-
P_3	2	1	Exp	44.328 h	-
process k			**MTTR** distrib	**MTTR** $\mathbb{E}$	**MTTR** $\mathbb{D}$
P_1			log-norm	3.60 h	11.43 h
P_2			log-norm	1.65 h	3.80 h
P_3			log-norm	4.925 h	12.94 h

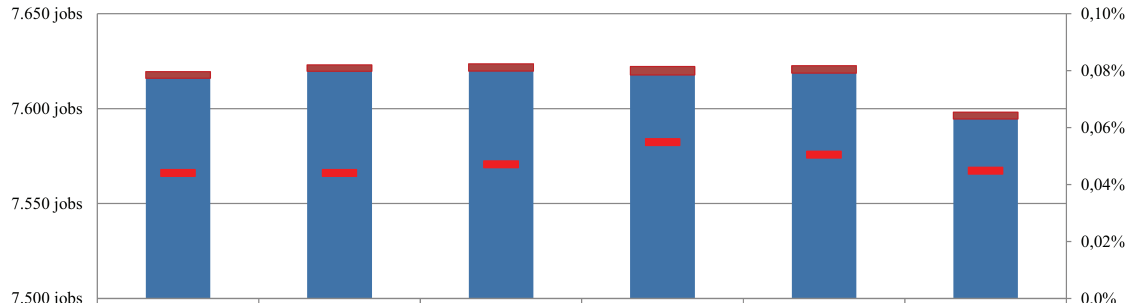
Table 4: Flow specifications from the second example.

	$\mathbf{R_1}$	$\mathbf{R_2}$	$\mathbf{R_3}$	$\mathbf{R_4}$
$o = 1$: process	$g(R_1, 1) = P_1, W_{P_1}$	$g(R_2, 1) = P_2, W_{P_2}$	$g(R_3, 1) = P_2, W_{P_2}$	$g(R_4, 1) = P_3, W_{P_3}$
$o = 1$: $p_{j,1}$	113min/job	20 min/job	20 min/job	8min/job
$o = 2$: process	$g(R_1, 2) = P_3, W_{P_3}$	$g(R_2, 2) = P_3, W_{P_3}$	$g(R_3, 2) = P_3, W_{P_3}$	-
$o = 2$: $p_{j,2}$	33 min/job	8 min/job	8 min/job	-
job distrib	log-norm	log-norm	log-norm	log-norm
$r_j\,(i = f(j))$	$\mathbb{E} = 31.9$ min	$\mathbb{E} = 126.6$ min	$\mathbb{E} = 42.6$ min	$\mathbb{E} = 15.95$ min
	$\mathbb{D} = 60.0$ min	$\mathbb{D} = 224.0$ min	$\mathbb{D} = 75.0$ min	$\mathbb{D} = 27.0$ min
$\omega_j\,(i = f(j))$	3	2	1	1
T	$\{(R_1, 1, 2)\}$	$\{(R_2, 1, 2)\}$		
timelink	$t_{(R_1,1,2)} = 6$ h	$t_{(R_2,1,2)} = 20$ h	-	-

4.2 Results of the Robustness Analysis

Each example was tested with five different data sets, where each data set was simulated ten times. Additionally, each MIP had 10 seconds for each iteration, in order to find a good gate decisions. This results for the CPLEX runtime at the first example in a average duality gap of 0.1260 with an average of 12.49 lots per instance and for the second example in a average duality gap of 0.0388 with an average of 15.69 lots per instance. The simulation range was 110 days, with a warm up period of 10 days.

The mean results of the first example are shown in Figure 8. The first bar, as with the first bars in Figure 10 for the second example, shows the mean result without modified job or tool release dates. This means that all release dates are known for the coming hour. Tool interruptions were the only unknown. For this reason, this slots serve as a reference value. The average modification with the normal distribution of job release dates and tool release dates have a similar output of finished jobs, and a similar ratio of time violations. Hence, it appears that from the inability to predict job or tool release dates has no significant influence of the quality of schedules. The modifications of job and tool release dates, using the normal



	MIP range 1h calc. time 10s	MIP job release dates disturbed 10x100days normal distrib. range 1h calc. time 10s	MIP tool release dates disturbed 10x100days normal distrib. range 1h calc. time 10s	MIP job and tool disturbed 10x100days normal distrib. range 1h calc. time 10s	MIP job and tool disturbed 10x100days uniform distrib. range 1h calc. time 10s	MIP job and tool disturbed 10x100days log-normal distrib. range 1h calc. time 10s
Avrg. finished jobs of R1 with time violation	3,40	3,44	3,72	4,36	3,94	3,52
Avrg. finished jobs of R1 without time violation	7.616,00	7.619,62	7.619,80	7.617,76	7.618,66	7.594,56
Avrg. finished jobs of R1	7.619,40	7.623,06	7.623,52	7.622,12	7.622,60	7.598,08
Avrg. finished jobs of R2	12.059,60	12.060,06	12.061,10	12.060,24	12.059,22	12.023,64
ratio of time violations	0,04%	0,04%	0,05%	0,05%	0,05%	0,04%
Avrg. workload WC1	76,51%	76,52%	76,53%	76,52%	76,52%	76,91%
Avrg. workload WC2	88,29%	88,34%	88,34%	88,33%	88,33%	88,06%
Avrg. R1 waittime at Gate	15,25 h	15,22 h	15,14 h	15,32 h	15,36 h	18,56 h

Figure 8: Average robustness analysis results for 5 data samples over 100 days using the first example.

and uniform distribution have similar outputs and a slightly higher time violation. Normally, it increases the likelihood that a job or tool is delayed. Therefore, the release dates are also modified by a log-normal distribution. According to this analysis, there are less time violations, but the output and cycle-time deteriorated slightly. The smaller output can be partially due to the decreased input, which is the result of delayed jobs. Nevertheless, for the simplistic example, the computed schedules are robust with regards to the average. The minor time violations for the generated schedules are a positive result of this research endeavor. A detailed look at the ratio of time violation diversifications is shown as a boxplot in Figure 9. It turns out that the average ratio of time violations by the simulations are slightly higher than the referenced value in the first slot. Furthermore, these boxplots illustrate that for datasets 1, 3 and 5 the deviation is in the range of $\pm 10\%$, and datasets 2 and 4 have only a few outliers. This can be explained by the fact that datasets 2 and 4 have a smaller workload. The scheduler can fix inaccuracies in the next computation by accounting for this. It can also be assumed that a higher workload results in a higher sensitivity to disturbances.

Figure 10 shows the mean robustness results of the second example. Here the ratio of time violations from products on route R_1 is much higher than the ratio of time violations in the first example. Furthermore, the ratio of time violations has a slightly higher variation than before. Based on the results of the first example and the fact that the whole second example underlies a very high workload, especially at work center W_3, it appears that a higher workload results in a higher sensitivity to disturbances. The output in this example is almost identical for each modification. This is also true for the log-normal distributed release dates. The time violations are minor at route R_2, even with disturbances. This fact may be explained by the relative long time constraint of 20 hours. This suggests thats the time constraint for route R_2 between process 2 and 3 may not need to reviewed. In Figure 11, the detailed ratio of the time violation range for the five different datasets is shown. The ratio of time violations for route R_1 is in most cases higher than the reference value which indicates that route R_1 is sensitive to disturbances, whereby route R_2 has only some outliers. Additionally, these boxplots show that the deviations are generally in a range of $\pm 10\%$. Based on this, it can be assumed that the schedules generated for the second example are robust.

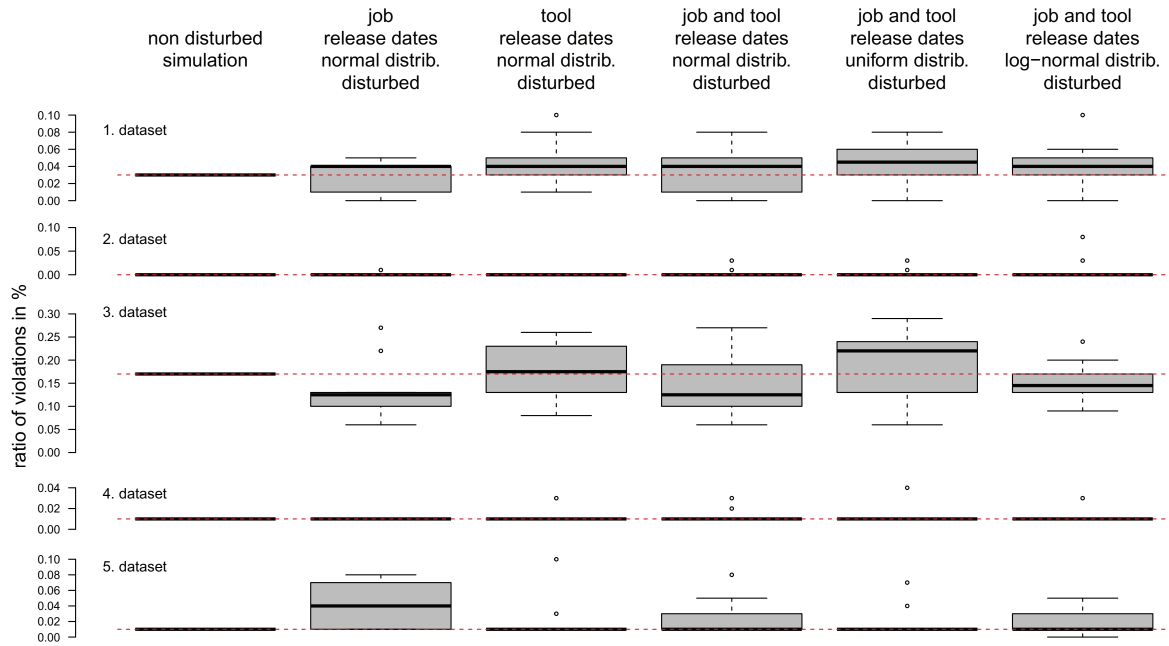
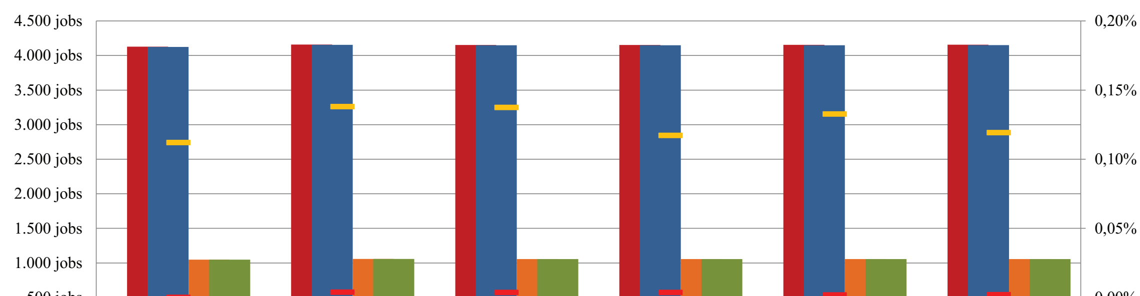


Figure 9: Detailed ratio of time violation diversifications for the first example.



	MIP range 1h calc. time 10s	MIP job release dates disturbed 10x100days normal distrib. range 1h calc. time 10s	MIP tool release dates disturbed 10x100days normal distrib. range 1h calc. time 10s	MIP job and tool disturbed 10x100days normal distrib. range 1h calc. time 10s	MIP job and tool disturbed 10x100days uniform distrib. range 1h calc. time 10s	MIP job and tool disturbed 10x100days log-normal distrib. range 1h calc. time 10s
Avrg. finished jobs of R1 with time violation	4,60	5,76	5,76	4,90	5,56	5,00
Avrg. finished jobs of R1	4.129,00	4.159,64	4.153,50	4.153,10	4.155,10	4.155,86
Avrg. finished jobs of R1 without time violation	4.124,40	4.153,88	4.147,74	4.148,20	4.149,54	4.150,86
Avrg. finished jobs of R2 with time violation	0,00	0,04	0,04	0,04	0,02	0,02
Avrg. finished jobs of R2	1.047,40	1.057,92	1.055,70	1.055,96	1.056,16	1.056,68
Avrg. finished jobs of R2 without time violation	1.047,40	1.057,88	1.055,66	1.055,92	1.056,14	1.056,66
Avrg. finished jobs of R3	3.127,20	3.148,76	3.143,86	3.143,84	3.144,10	3.145,72
Avrg. finished jobs of R4	8.307,20	8.368,66	8.357,42	8.358,00	8.358,80	8.361,96
Avrg. workload WC1	87,81%	88,45%	88,32%	88,31%	88,35%	88,37%
Avrg. workload WC2	34,11%	34,37%	34,32%	34,32%	34,32%	34,34%
Avrg. workload WC3	89,40%	90,06%	89,93%	89,93%	89,96%	89,98%
Avrg. R1 waittime at Gate	104,36 h	95,40 h	96,96 h	97,30 h	97,18 h	96,63 h
Avrg. R2 waittime at Gate	93,13 h	84,41 h	85,56 h	86,13 h	86,08 h	85,56 h
R1 ratio of time violations	0,11%	0,14%	0,14%	0,12%	0,13%	0,12%
R2 ratio of time violations	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%

Figure 10: Average robustness analysis result for 5 data samples over 100 days of the second example.

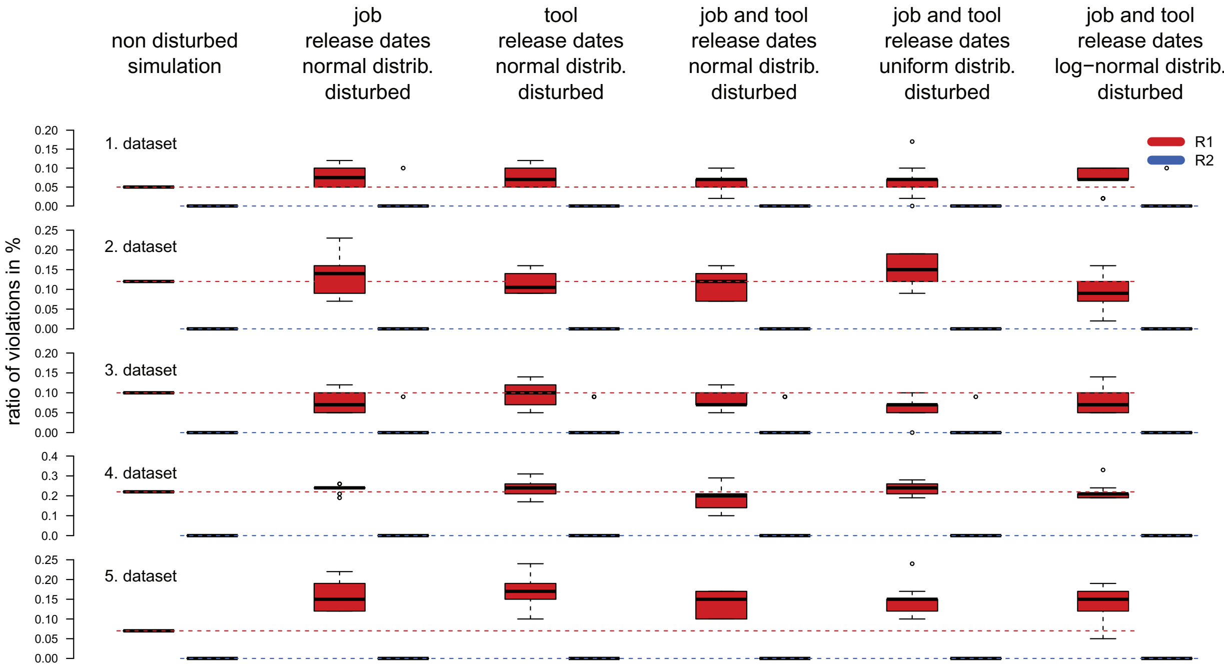


Figure 11: Detailed ratio of time violation diversifications in the second example.

5 CONCLUSION AND OUTLOOK

In this paper, an MIP with time constraints was presented which generates schedules that are resistant to tool interruptions. The availability of tools with consideration of the lifespan of tools was integrated into the time constraints. This downscales the capacity of a production area, which should minimize the ratio of time violations. By the test of robustness with modified job and tool release dates, it turns out that the MIP provides excellent solutions with a minimum number of time violations. The computed results seem robust to disturbances in release dates. Based on the small sample and the complexity of different production lines in semiconductor industry, further production line testing is indicated. It is also advisable to check different distribution combinations and different, as well as higher, deviations.

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