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OPTIMIZING CAPACITY ASSIGNMENT OF MULTIPLE IDENTICAL METROLOGY TOOLS

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ABSTRACT

In modern semiconductor manufacturing facilities, metrology capacity is becoming limited because of the high equipment cost. This paper studies the problem of optimally assigning the capacity of multiple identical metrology tools in order to minimize the risk of defective wafers on heterogeneous production machines. We assume that the output of each production machine is assigned to only one metrology tool. The resulting problem is formulated as a Multiple Choice Multiple Knapsack Problem (MCMKP), which combines the Multiple Choice Knapsack Problem and the Multiple Knapsack Problem and does not appear to have been studied in the literature. A greedy heuristic and an improving heuristic are also proposed. Numerical experiments are performed on randomly generated instances to analyze and compare the solutions of the heuristics with solutions obtained with a standard solver.

1 INTRODUCTION

Recently, due to increasing metrology equipment cost, in line quality control has become a scarce resource. As a result, the level of monitoring desired by quality engineers is not always practicable. Tightening the control of one product or machine often requires reducing the monitoring level on another. Many aspects of metrology policy in semiconductor manufacturing plants (fabs) have been studied both by practitioners and researchers (Lee et al. (2003); Dauzère-Pérès et al. (2010); Colledani and Tolio (2011); Shanoun et al. (2011); Nduhura-Munga et al. (2012); Bettayeb et al. (2012); Nduhura-Munga et al. (2013); Rodriguez-Verjan et al. (2013); Gilenson, Hassoun, and Yedidsion (2015)).

In a previous publication (Dauzère-Pérès, Hassoun, and Sendon (2016)), we study the problem of optimizing the sampling rates of several production machines competing for the capacity of a unique and reliable metrology tool. The production machines are characterized by their failure rates, their throughput rates, and their consumption of the metrology capacity. In the resulting optimization problem, the expected product loss is minimized subject to the constraint related to metrology capacity. The decision variables are the sampling periods of the production machines. The problem is then reformulated as a Multiple Choice Knapsack Problem (MCKP), for which several heuristics are proposed based on the work of Sinha and Zoltners (1979) and Pisinger (1995).

While in fabs several production machines are sometimes monitored by a unique metrology tool, it is often the case that several metrology tools can perform the same control operation. A model with several metrology tools prompts the question of which tool will be partially or fully assigned to the inspection of a production machine. Metrology tools can also differ in terms of inspection rate, reliability or qualification. In this paper, we formulate the case of multiple identical metrology tools where the inspection of lots from a production machine is assigned toa single metrology tool (Section 2). We introduce an Integer Linear Programming model that can be solved with a standard solver. This model corresponds to a Multiple Choice Multiple Knapsack Problem (MCMKP). As far as we know, the MCMKP has never been studied in the literature. We then propose fast heuristics to solve the problem (Section 3). Computational results on randomly generated instances are reported and discussed in Section 4.

2 MATHEMATICAL MODEL

Several identical metrology tools $t = 1,\dots,T$ inspect the output of several production machines $r = 1,\dots,R$. The production machines are modeled as Bernoulli experiments, and differentiated by their probability of failure p_r. Let TP_r denote the throughput rate of the production machines and TM_r the throughput rate of a metrology tool when inspecting lots processed on machine r. We refer to the number of production cycles on machine r between two consecutive inspections as the sampling period SP_r. The inspection is assumed to be perfect, i.e. the diagnosis provided by the metrology tool is always right. We assume that one and only one metrology tool is assigned to the inspection of the totality of the production of each machine, and thus $T \leq R$.

The decision variables are the sampling periods SP_r and the assignment of machine r to metrology tool t, modeled using a binary variable v_r^t, $\forall\, r = 1,\dots,R$, $\forall\, t = 1,\dots,T$. The values of these variables determine both the expected throughput of bad lots from production tool r, and its share in the consumption of the capacity of the metrology tools, denoted by $g_r(SP_r)$. There is also a maximum value SP_r^{max} over which the quality control is unacceptable.

Following a decision to inspect products r at rate SP_r, wafers are reworked or scrapped at a certain rate $WL_r(SP_r)$ formalized later in this paper. We assume that the production of a machine in good condition is perfect, while that of a defective machine is fully reworked or scrapped. This classical worst-case assumption can be relaxed in our approach by assuming that only a given percentage of the production is reworked or scrapped. There is no difference between the value of lots on the different machines. As a consequence, we strive to minimize the expected overall production rate of defective lots.

Hence, the optimization problem (P) can be formulated as:

$$\min \sum_{r=1}^{R} WL_r(SP_r) \tag{1}$$

s.t.

$$\sum_{r=1}^{R} g_r(SP_r) v_r^t \leq 1 \qquad \forall\, t = 1,\dots,T \tag{2}$$

$$\sum_{t=1}^{T} v_r^t = 1 \qquad \forall\ r = 1,\ldots,R \tag{3}$$

$$SP_r \in 1,\ldots,SP^{max} \quad \forall r \in 1,\ldots,R \tag{4}$$

$$v_r^t \in \{0,1\} \qquad \forall\ r = 1,\ldots,R; \quad \forall\ t = 1,\ldots,T \tag{5}$$

The fraction of capacity consumed on a metrology tool by machine r for a given sampling period SP_r (assuming that the same metrology tool is assigned to measure all lots sampled from r) can be written:

$$g_r(SP_r) = \frac{TP_r}{SP_r TM_r} \tag{6}$$

A sampling period on tool r is, in our representation, a series of SP_r Bernoulli experiments, each of which corresponds to the production of a lot. If a failure occurs in the first production cycle, all the following SP_r lots (the number of lots produced until the next inspection takes place) are defective. Similarly, if a failure occurs in the second production cycle, $SP_r - 1$ lots will be defective, and so on. A failure occurring in the last production cycle before inspection, will yield only one defective lot. The expected number of bad lots between two inspections is therefore given by:

$$SP_r p_r + (SP_r - 1)(1-p_r)p_r + \cdots + 1(1-p_r)^{SP_r - 1} p_r = p_r \sum_{i=0}^{SP_r - 1} (SP_r - i)(1-p_r)^i$$

With $\frac{TP_r}{SP_r}$ being the rate at which inspection is performed at the station, the overall expected rate of defective lots produced by machine r with an inspection policy using sampling period SP_r, and referred to as Wafer Loss, can be written as (see (Dauzère-Pérès, Hassoun, and Sendon 2016)):

$$WL_r(SP_r) = \frac{p_r TP_r}{SP_r} \sum_{i=0}^{SP_r - 1} (SP_r - i)(1-p_r)^i \tag{7}$$

As in (Dauzère-Pérès, Hassoun, and Sendon 2016), (P) can be rewritten as an Integer Linear Program (ILP) since, for each machine r, SP_r must be chosen in the set of all possible sampling periods $\{1,\ldots,SP_{max}\}$. However, in our problem, we also need to assign each production machine to one and only one metrology tool. Let us define the binary variable $w_r^{s,t}$, where $w_r^{s,t} = 1$ if metrology tool t is assigned to control the production of machine r with a sampling rate $SP_r = s$, and 0 otherwise. The ILP can be stated as:

$$\min \sum_{t=1}^{T} \sum_{r=1}^{R} \sum_{s=1}^{SP^{max}} WL_r(s) w_r^{s,t} \tag{8}$$

s.t.

$$\sum_{t=1}^{T} \sum_{s=1}^{SP^{max}} w_r^{s,t} = 1 \qquad \forall r = 1,\ldots,R, \tag{9}$$

$$\sum_{r=1}^{R} \sum_{s=1}^{SP^{max}} g_r(s) w_r^{s,t} \leq 1, \quad \forall\ t = 1,\ldots,T, \tag{10}$$

$$w_r^{s,t} \in \{0,1\} \qquad \forall r = 1,\ldots,R;\ t = 1,\ldots,T;\ s = 1,\ldots,SP^{max}. \tag{11}$$

Constraints (9) ensure that exactly one sampling rate s and exactly one metrology tool t are selected for each production machine r. Constraints (10) guarantee that the capacity constraint of each metrology tool is satisfied. The ILP can be solved using a standard solver but also with the heuristics that we propose in the following section. The performance of these heuristics on randomly generated instances compared to the standard solver is analyzed in Section 4.

3 HEURISTICS

Our first heuristic, which we shall refer to as H_1 for the remainder of this paper, aggregates all metrology tools into one, whose capacity is equal to T, i.e. Constraints (10) in the ILP is replaced with:

$$\sum_{t=1}^{T}\sum_{r=1}^{R}\sum_{s=1}^{SP^{max}} g_r(s) w_r^{s,t} \leq T. \tag{12}$$

The resulting problem is a Multi-Choice Knapsack Problem (MCKP). We solve it using the simple rounding heuristic proposed in (Dauzère-Pérès, Hassoun, and Sendon 2016), which is based on the linear relaxation of the problem (LMCKP). The LMCKP is solved optimally using the greedy heuristic proposed in (Pisinger 1995) whose complexity is $O(nlogn)$ (where $n = R.SP^{max}$ in our case). Based on the sampling rates SP_r obtained by heuristically solving the MCKP, a greedy heuristic is then applied to build a feasible solution. At each iteration, the process machine r not already assigned to a metrology tool which consumes the largest metrology capacity is assigned to the metrology tool t with the largest remaining capacity. If the capacity of t is exceeded, then SP_r is increased until either the capacity of t is enough or $SP_r = SP^{max}$. In the latter case, it means that the solution is not feasible.

Note that, with only one metrology tool, Heuristic H_1 reduces to Heuristic 1 in (Dauzère-Pérès, Hassoun, and Sendon 2016). The detailed description of Heuristic 1 is provided in Algorithm 1. Its worst case time complexity is $O(\max(R.SP^{max}log(R.SP^{max}), R.T.SP^{max}))$, which can probably be reduced to $O(R.SP^{max}log(R.SP^{max}))$.

Algorithm 1 Heuristic H_1

Let $\mathscr{F}$ be the set of fixed pairs (machine, sampling period). $\mathscr{F} \leftarrow \emptyset$.
Determine $\mathscr{F}$ by solving the MCKP for the problem where (10) is replaced by (12) with the first rounding heuristic of (Dauzère-Pérès, Hassoun, and Sendon 2016).
Let $\mathscr{G}$ be the set of fixed triplets (machine, sampling period, metrology tool). $\mathscr{G} \leftarrow \emptyset$.
Let $Capa_t$ be the capacity used on metrology tool t. $Capa_t = 0$, $t \in 1, \ldots, T$.
while $\mathscr{F} \neq \emptyset$ **do**
  Find the process machine r, such that $\exists (r,s) \in \mathscr{F}$, with the largest metrology capacity $g_r(s)$.
  Find the metrology tool t with the largest remaining capacity, i.e. with the smallest $Capa_t$.
  if $Capa_t + g_r(s) \leq 1$ **then**
    Assign r to t with sampling rate s, i.e. $\mathscr{G} \leftarrow \mathscr{G} \cup \{(r,s,t)\}$ and $Capa_t = Capa_t + g_r(s)$.
  else
    Increase s until either $Capa_t + g_r(s) \leq 1$ or $s = SP^{max}$
    if $Capa_t + g_r(s) \leq 1$ **then**
      Assign r to t with sampling rate s, i.e. $\mathscr{G} \leftarrow \mathscr{G} \cup \{(r,s,t)\}$ and $Capa_t = Capa_t + g_r(s)$.
    else
      Assign r to t with sampling rate SP^{max}, i.e. $\mathscr{G} \leftarrow \mathscr{G} \cup \{(r, SP^{max}, t)\}$, $Capa_t = 1$ and the problem is infeasible.
    end if
  end if
  $\mathscr{F} \leftarrow \mathscr{F} - \{(r,s)\}$.
end while

We also developed an improving heuristic described in Algorithm 2. Based on the product assignment to metrology tools determined in Heuristic H_1, a Multi-Choice Knapsack Problem is solved for each metrology tool. This is done with Heuristic 2/3 (combining two heuristics) proposed in (Dauzère-Pérès, Hassoun, and Sendon 2016) which was shown to be effective. The new solution for each metrology tool is only kept if it improves the current solution. Heuristic H_1 combined with the improving heuristic is called H_1^+ in the remainder on the paper.

Algorithm 2 Improving heuristic

Let $\mathscr{G}$ be a set of fixed triplets (machine, sampling period, metrology tool) determined by Heuristic 1, i.e. $\exists s \in 1,\ldots,SP^{max}$ and $\exists t \in 1,\ldots T$ such that $(r,s,t) \in \mathscr{G}$, $\forall r \in 1,\ldots,R$.
for $t \in 1,\ldots,T$ **do**
  Set $\mathscr{G}' \leftarrow \mathscr{G}$.
  Solve a Multi-Choice Knapsack Problem with Heuristic 2/3 of (Dauzère-Pérès, Hassoun, and Sendon 2016) for the process machines r assigned to metrology tool t, i.e. $\exists s \in 1,\ldots,SP^{max}$ such that $(r,s,t) \in \mathscr{G}$.
  Update $\mathscr{G}'$ with the new sampling rates for metrology tool t.
  if $\sum_{r=1}^{R} \sum_{s=1;\ (r,s,t)\in\mathscr{G}'}^{SP^{max}} WL_r^t(s) < \sum_{r=1}^{R} \sum_{s=1;\ (r,s,t)\in\mathscr{G}}^{SP^{max}} WL_r^t(s)$ **then**
    $\mathscr{G} \leftarrow \mathscr{G}'$
  end if
end for

Note that the improving heuristic can be applied to any feasible solution, and that its time complexity is at most also $O(R.SP^{max})$, i.e. Heuristic H_1^+ does not increase the complexity of Heuristic H_1.

4 COMPUTATIONAL EXPERIMENTS

In this section, we analyze the performance of Heuristics H_1 and H_1^+ on numerous randomly generated instances, and the results of H_1 and H_1^+ are compared with the results obtained with the ILP and the standard solver IBM ILOG CPLEX 12.6. Because our heuristics run in less than 1 second for each instance, we decided to limit the standard solver to 60 seconds. Since the optimal solution is not always obtained, we provide the lower bound (LB) and the upper bound (UB) given by IBM ILOG CPLEX after 60 seconds.

The number of production machines is chosen from the set $\{5,10,20,40\}$, and the number of metrology tools from the set $\{3,5\}$. The characteristics of each machine r are defined as follows. The probability of failure p_r is generated from a uniform distribution $U[p_{min};p_{max}]$, where p_{min} is kept constant $(p_{min} = 0.01)$ and p_{max} is chosen from the set $\{0.05,0.2\}$. The throughput rate TP_r is generated from a uniform distribution $U[TP_{min};TP_{max}]$, where $TP_{max} = 1,000$ and TP_{min} is chosen from the set $\{100,900\}$. The measurement rate TM_r is determined using the ratio $\frac{R \cdot \overline{TP}}{T \cdot TM_r}$ chosen from the set $\{5,10,30\}$, where $\overline{TP}$ is the average throughput rate for the considered scenario. Finally, we set $SP^{max} = 500$ for all machines so that it is not constraining. Combining these parameters leads to 96 scenarios.

Finally, in order to limit the impact of extreme non-representative parameter combinations, 30 instances are generated for each scenario, each with different randomly generated values of p_r and TP_r. Therefore, a total of 2,880 different problem instances were solved.

Table 1 presents the number of instances, out of a total of 360 (for each combination of R and T), for which Heuristic H_1 finds a feasible solution. As expected, the only case where a feasible solution is always found is when $R = T$. However, H_1 finds a feasible solution in the vast majority of the instances.

H_1^+ improves over H_1 in several ways. First, no matter the instance characteristics, H_1^+ always finds a feasible solution. Table 2 presents the improvement in the objective function achieved by H_1^+ over H_1 (only for instances for which H_1 finds a feasible solution). Note that the improvement achieved by H_1^+ is noticeable. The largest gains are obtained for low values of R and T, for which the capacity $g_r(s)$ is usually the largest, thus leading to large increase of s, and thus of the wafer loss, to make the solution feasible in H_1. In all scenarios, there are at least some instances for which H_1^+ does not improve over H_1.

Table 1: Number of feasible solutions (out of 360) determined by H_1.

	T	
R	3	5
5	351	360
10	356	355
20	349	353
40	333	349

Table 2: Comparison between H_1 and H_1^+.

		T	
R		3	5
5	Avg	2.6%	0%
	Max	7.3%	0%
10	Avg	2.3%	1.1%
	Max	8.5%	6.1%
20	Avg	0.9%	0.4%
	Max	2.6%	1.8%
40	Avg	0.7%	0.2%
	Max	2.3%	1%

Having determined that H_1^+ strongly dominates H_1, only the performances of H_1^+ are now analyzed. Table 3 compares the results of H_1^+ to the upper bounds of the standard solver. We separate the cases where $LB = UB$ ("Opt.", the solution obtained by the standard solver is guaranteed to be optimal) and where $LB \neq UB$ ('Non-opt."). Note that, when $T = R = 5$, both the standard solver and H_1^+ give optimal solutions. This comes as no surprise, since each metrology tool can be fully dedicated to one production machine. The optimal solution consists in filling the metrology capacity of each tool, and is therefore straightforward. Some instances, in particular those with lower values of R and T, are more challenging for the heuristic when $LB = UB$. For $R = 3$, in the worst case, H_1^+ yields a solution with an expected wafer loss which is larger than the optimum by 6.4% for $R = 5$ and 3.4% for $R = 10$. However, on average, the performance of H_1^+ is excellent. Note also that, when $LB \neq UB$ and in some cases, H_1^+ finds a better solution than the standard solver. In all cases but one, the minimum difference is negligible.

Table 3: Comparison between H_1^+ and UB.

		T			
		3		5	
R		Non-opt.	Opt.	Non-opt.	Opt.
5	Avg.	0.2%	0.7%		0%
	Min.	0%	0%		0%
	Max.	0.4%	6.4%		0%
10	Avg.	0.4%	0.9%	0.2%	0.9%
	Min.	0%	0%	-0.1%	0%
	Max.	2%	3.4%	1.7%	3.7%
20	Avg.	0.1%	0.5%	0.4%	1%
	Min.	0%	0%	0%	0.2%
	Max.	0.9%	1.5%	1.8%	2%
40	Avg.	0.1%	0.2%	0.1%	0.4%
	Min.	0%	0%	0%	0.2%
	Max.	0.3%	0.6%	0.7%	0.6%

In the next three tables (4 to 6), we break down the results by the scenario characteristics. The tables present the impact of the ratio $\frac{R \cdot \overline{TP}}{T \cdot TM_r}$, of TP_{min} and of p_{max} on the average performance of H_1^+ compared to the upper bounds provided by the standard solver. The results seem excellent across the board, confirming the robustness of H_1^+ when faced with very different scenarios.

Table 4 prompts some remarks. First, the higher $\frac{R \cdot \overline{TP}}{T \cdot TM_r}$, the better the results of H_1^+. This is explained by the fact that higher $\frac{R \cdot \overline{TP}}{T \cdot TM_r}$ values lead to a higher stress on the metrology capacity, thus larger values of the sampling periods, and therefore smaller differences for $WL_r(s)$ between different values of s, which allows a solution closer to the optimal solution to be found.

Table 4: Impact of *Ratio* on the comparison between H_1^+ and UB.

		Ratio		
R	T	5	10	30
5	3	1.3%	0.6%	0.1%
	5	0%	0%	0%
10	3	1.2%	0.7%	0.3%
	5	1.3%	0.7%	0.2%
20	3	0.6%	0.3%	0.1%
	5	0.8%	0.4%	0.1%
40	3	0.2%	0.1%	0%
	5	0.3%	0.1%	0%

In order to discuss the next two tables, let us recall that the values of TP_r are randomly chosen between TP_{min} and $TP_{max} = 1000$, which means that, with $TP_{min} = 900$, the values of the production rates are not only larger, but also that the range of allowed production rates in the instance is greatly reduced compared to the case where $TP_{min} = 100$. The same holds with the failure probabilities. Since $p_{min} = 0.01$, scenarios characterized by $p_{max} = 0.05$ allow for a narrower range of values. In both tables, these scenarios (with similar machines) seem to be more challenging for our heuristic.

Table 5: Impact of TP_{min} on the comparison between H_1^+ and UB.

		TP_{min}	
R	T	100	900
5	3	0.4%	0.9%
	5	0%	0%
10	3	0.6%	0.9%
	5	0.7%	0.8%
20	3	0.2%	0.4%
	5	0.4%	0.4%
40	3	0.1%	0.1%
	5	0.1%	0.1%

Table 6: Impact of p_{max} on the comparison between H_1^+ and UB.

		p_{max}	
R	T	0.05	0.2
5	3	0.7%	0.6%
	5	0%	0%
10	3	0.9%	0.5%
	5	0.8%	0.6%
20	3	0.4%	0.2%
	5	0.5%	0.4%
40	3	0.1%	0.1%
	5	0.2%	0.1%

To confirm our previous analysis, Table 7 presents, for each separate combination of R and T, the results for each pair of values p_{max} and TP_{min}. Our heuristic consistently performs best when $p_{max} = 0.2$ and $TP_{min} = 100$, i.e. when the dissimilarity between machines is the greatest. The worst performance of H_1^+ is observed in the opposite situation, i.e. when $p_{max} = 0.05$ and $TP_{min} = 900$.

Table 7: Impact of machine similarity on the comparison between H_1^+ and UB.

		TP_{min}			
		100		900	
		p_{max}		p_{max}	
T	R	0.05	0.2	0.05	0.2
3	5	0.41%	**0.37%**	0.98%	0.89%
	10	0.67%	**0.48%**	1.15%	0.58%
	20	0.26%	**0.17%**	0.52%	0.31%
	40	0.10%	**0.06%**	0.18%	0.09%
5	5	0%	0%	0%	0%
	10	0.74%	**0.64%**	0.88%	0.66%
	20	0.44%	**0.36%**	0.47%	0.39%
	40	0.14%	**0.08%**	0.17%	0.11%

5 CONCLUSION

Extending our previous work to model capacity allocation of a single metrology tool to unreliable production machines, this paper studied the case of multiple identical metrology tools. We assumed that no partial allocation is allowed, i.e. that each production machine is assigned to a unique metrology tool. The problem was modeled as a Multiple-Choice Multiple Knapsack Problem which, to the best of our knowledge, has never been addressed in the literature. Two heuristics were proposed and compared on randomly generated instances to the resolution of an Integer Linear Program with a standard solver.

We are pursuing this work by including different extensions. In particular, we study how to consider heterogeneous and unreliable metrology tools, and also that the metrology capacity required by a production machine can be shared among multiple metrology tools. These extensions increase the complexity of the problem, in terms of changes both in the objective functions and the constraints. Moreover, a Decision Support System that includes our heuristics is being developed with our industrial partner.

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