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DYNAMIC SAMPLING FOR RISK MINIMIZATION IN SEMICONDUCTOR MANUFACTURING

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ABSTRACT

To control the quality of their processes, manufacturers perform measurement operations on their products. In semiconductor manufacturing, measurement capacity is limited because metrology tools are expensive, thus only a limited number of lots of products can be measured. Selecting the set of lots to control to minimize risk is called sampling. This work studies the problem of optimizing the sampling to minimize the number of wafers at risk on production machines in semiconductor manufacturing.

1 INTRODUCTION

In this paper, we study the problem of optimally sampling a set of lots to measure to minimize the risk on production machines in semiconductor manufacturing. Providing efficient approaches for this problem is critical in the industry because of the operational constraints on the measurement tools. Control operations are becoming more and more costly as technology improves. We formulate the sampling problem in semiconductor manufacturing as the budgeted maximization of a submodular function that describes the industrial environment. We explore integer linear programming models with cardinal, knapsack and multiple knapsack capacity constraints; analyze the performances of a greedy algorithm and a local search by comparing them to the integer linear programs solved by a standard solver on industrial instances and randomly generated instances.

2 RISK MODELING IN SEMICONDUCTOR MANUFACTURING

In semiconductor manufacturing, the following hypotheses are verified:

1. The failure mode of a production machine is irreversible, a machine that starts to shift does not return to its normal behavior without maintenance.
2. Measurements are always correct; there are no false positives or false negatives.

Then, for a given list of elements generating risk in the factory we count the number of wafers produced between two control operation, this number is known as W@R for wafers at risk, since the status of these items is unknown and they could be scrapped or reworked. Monitoring W@Rs over the factory is therefore directly linked to the sampled lots in metrology. The literature review (Nduhura-Munga et al. 2013) splits the different strategies used to optimize the sampling in semiconductor into three categories:

1. Static: rule based, for example: one lot every 10 lots processed on the machine will be measured. The main advantage is that static rules are easy to implement.
2. Adaptive: adaptive sampling rules mostly enhance the static rules by computing them based on some knowledge of the schedule plan or machine failure modes.
3. Dynamic: model the industrial environment with an indicator and decide in real time which lots should be measured, this paper focuses on dynamic sampling methods.

In particular we use indicators like the Global Sampling Indicator (GSI) to aggregate W@Rs for all risks and model in real time the total risk level in the industrial environment (Dauzere-Péres et al. 2010).

3 MODELING AND SOLVING THE SAMPLING PROBLEM

3.1 Modeling

Selecting a set of lots to minimize the GSI can be formulated as the maximization of a submodular set function subject to a capacity constraint. We considered three types of capacity constraints: multiple knapsack, knapsack, and cardinal. The simplest case with a cardinal capacity constraint was formulated as a linear program and proved to be NP-hard in (Cornnejols et al. 1977). The linear programs for knapsack and multiple knapsack capacity constraint are derived from this known case.

Standard heuristics were built to be compared to the linear program; we considered the greedy algorithm (Edmonds 1971) and an exchange procedure as a local search.

3.2 Solving

We conducted computational experiments on industrial instances to compare the efficiency of standard greedy heuristics and of the linear programs run on an open source solver (CBC-COIN-OR) with 3 minutes of running time. Table 1 summarizes the average approximation and the proportion where the optimal solution was found by each algorithm. The performances are good enough for an industrial implementation and are being industrialized. To understand these high performances on large instances we generated pseudo-industrial instances derived from the industrial cases. The performances are similar and it shows that this method can be used to solve the sampling problem for other indicators modeling the environment.

Table 1 : Average results on the industrial instances.

Constraint type	**Average approximation ratio**			**Optimal solution found**		
	Greedy	**Exchange**	**Solver**	**Greedy**	**Exchange**	**Solver**
Cardinal	99.99%	100%	100%	99.71%	100%	100%
Knapsack	99.00%	99.10%	100%	52.19%	59.54%	100%
Multiple knapsack	79.52%	80.10%	100%	10.00%	10.00%	100%

4 CONCLUSION

The sampling problem in semiconductor manufacturing can be modeled as the maximization of a submodular set function subject to various types of capacity constraints. We compared the efficiency of standard heuristics and linear programming on industrial instances and showed that the performances are good enough for industrial implementations on three different types of instances. These methods are being deployed at Soitec to manage the dynamic sampling of lots in the 300mm factory. Using machine health indices to enhance the sampling decision and optimize the scheduling of the lots in metrology are being investigated as perspectives.

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