Simulation in Production
and Logistics 2015
Markus Rabe & Uwe Clausen (eds.)
Fraunhofer IRB Verlag, Stuttgart 2015

Scheduling under Consideration of the Machine Capability

Ablaufplanung unter Berücksichtigung der Maschinenfähigkeit

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Abstract: A high yield is extremely important for the costs of production and thus also the price and competitiveness. In this paper a scheduling method is presented, which takes machine parameters into account. This is done exemplary for a SMD manufacturing. Here, not all machines within a parallel work centre are assumed to be equal, even if they are capable to process the same products. Typically, some machines perform better than other machines. This machine performance could be described by a so called machine health parameter. Also, some products could be more important than other products. This may be defined i.e. by the number of PCB layers. The goal is to schedule more important products to those machines with the best health value. Doing so will increase yield for these products. For this, different dispatching rules and a mixed integer programming approach are compared within a simulation model for practical test data.

1 Introduction

Yield is important in every area of current productions. This statement is equally valid, whether a semiconductor factory or a SMD (surface mounted device) factory is considered for example. In literature many different approaches exist to maximize the yield. For example Wein (1992) investigated the correlation between yield and cycle time. Other approaches try to optimize time dependencies between product steps (Klemmt and Mönch 2012). Also for SMD manufactory many investigations regarding yield optimization are done (Wohlrabe 2008). An important lesson here, among other things, is the process capability and, consequently, the machine capability. This parameter indicates how well a machine is able to maintain certain accuracies in production (Fig. 1). The process capability then depends, among other things, on the amount of equipment involved in the process and their machine capabilities. Due to this fact, a preliminary study will be presented for yield optimized scheduling. Using the example of the aforementioned SMD manufacturing, SMD components are assembled on printed circuit boards (PCB). For this, typically multiple placement machines are available.

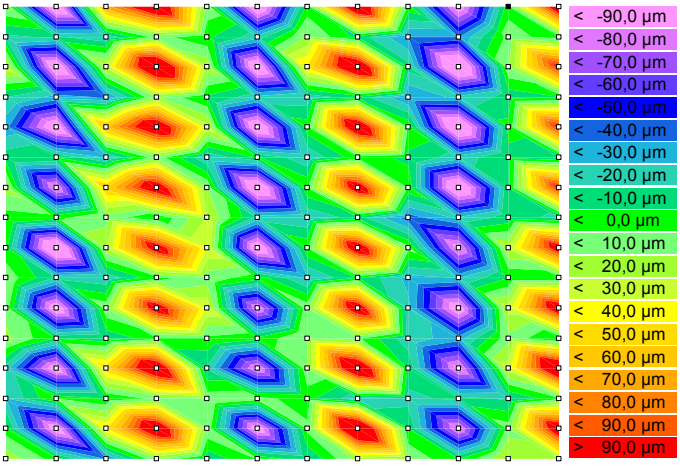

Figure 1: *Atlas accuracy of x-offset of a placement equipment (Wohlrabe 2008).*

Thereby not necessarily all machines are allowed for the placement of all components. Due to this there exists a dedication matrix, which defines the allowed machines for the different SMD devices. Furthermore there may be differences between the circuit boards, which should be equipped with the SMDs. These PCBs, for example, can differ between the numbers of layers (1-36) as well as the size and the complexity. Because of these differences, and thus also the cost of printed circuit boards, the products can be divided into high-priority and less prioritized products. Also the placement machines can have different machine capability values. These values may also depend on the product/machine combination. Now the task is to schedule the different products (PCB/SMD combinations) to the machines, whereby important products should be scheduled to machines with a high machine capability, respectively health value.

This problem could also be adapted to other production areas. For example, the complex production in the semiconductor manufacturing may take machine values into account to plan important or high cost products onto the best possible equipment. Since the production of today's chips in the semiconductor manufacturing partially takes up to three months and several hundred process steps (Potoradi et al. 2002; Yurtsever et al. 2009) until the completion of each layer, there is a large potential for optimization here.

In this paper the possible effect on using the provided machine health values should be estimated. Thereby the calculation of these health values is not taken into account here. The paper is structured as follows. In section 2 the problem is described. Section 3 is used to present the dispatching rules and define the mixed integer programming model. In section 4 the experimental setup is presented and afterwards in section 5 the results are shown. An outlook and conclusion is done in section 6.

2 Problem Description

The underlying work centre problem was derived from a practical point of view. A work centre with unrelated parallel machines is used as reference. Also an amount of jobs was created, whereby each job is assigned exactly to one product (PCB/SMD combination). Also each job has a release date and an operational due date (ODD), which defines the due date for the current operation. The defined products have a dedication matrix. This matrix contains the allowed machines for each product. Furthermore the products are divided into 2 groups – important products (IP) and normal products (NP). This classification is used for the yield integrated scheduling and the resulting objective function. The processing times differ for each product, whereby the processing time is equal for one product and different allowed machines. Each machine has a health value, which defines the actual health state of this machine. In this investigation this value is defined between zero and one. The health value is also assumed to be constant during the whole time horizon. This is done because of the simplicity of the model.

The schedules which are used to calculate the objectives are generated with a discrete event simulation model (Fig. 2). All properties, which are described within section 2, have been implemented in the simulation model.

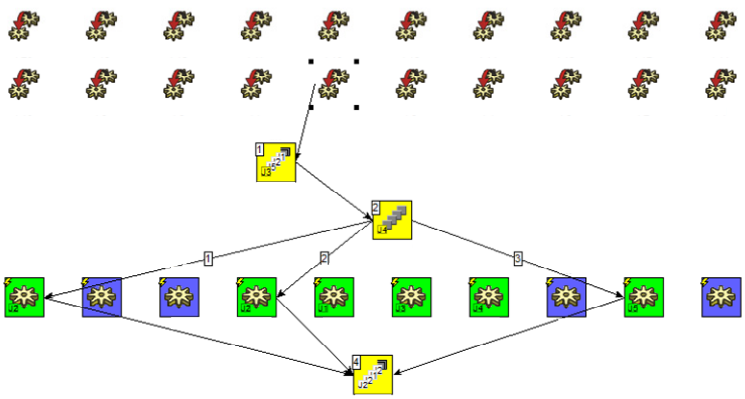

Figure 2: *Exemplary simulation model (simcron MODELLER)*

Also several dispatching rules are included within this simulation model. These different dispatching rules are compared with a mixed integer programming (MIP) approach. Furthermore, an interface was implemented where the results from the MIP model could be used.

The observed objectives in this investigation are:

- Flow factor – This is the ratio of the cycle time to the raw processing time
- Tardiness – The sum of delay for late jobs. Early jobs get a tardiness of zero
- Quality – This is defined as the sum of the machine health value for each important job processed on the corresponding machine

3 Methods

3.1 Dispatching Rules

As a reference, three different dispatching rules with different complexity are implemented:

- Operational due date - ODD
- Best Machine - BestM
- Practical rule - DePrio

The ODD rule is the simplest one. All jobs are ordered using their local operational due date. If a machine gets idle, the next allowed job regarding the due date is scheduled on this machine. Here no difference between important and non-important jobs is done. Also the health value of the machine is not observed. This rule is investigated by Rose (2003) and is usually used to minimize tardiness.

The next dispatching rule is called "Best Machine". Here for all important products only the machine with the highest health value is allowed. All other machines which are released for this product in the dedication matrix get locked. So these products could only be processed on the "best" machine out of the set of allowed machines. Furthermore, the sorting of the jobs is also done by the ODD rule. Additionally, all jobs of the important products get a priority state. This means, these jobs have a higher priority compared to the normal jobs. This is done because of the hardly reduced dedication matrix for the important products. Due to the nature of this dispatching rule, the result concerning the quality of the jobs is an upper bound for this objective.

The last used dispatching rule is a practical orientated rule called DePrio. Due to the confidentiality, the rule is not described in detail here. It works with priority based dispatching lists for every machine. Here also the ODD rule is used as basis. Furthermore, the jobs get an additional priority in the case of important products. But the priority is reduced for important jobs depending on the actual load and machine health value. So in contrast to the basic ODD rule, where one global dispatching list exists, each machine has an own dispatching list now, where the jobs are sorted by their priority value.

Because mathematical methods for scheduling get more and more practicable, also a mixed integer programming approach was investigated.

3.2 Mixed Integer Programming

A mathematical capacity planning model was implemented using mixed integer programming methods. In this subsection this mathematical model is described in detail and afterwards the coupling with the simulation model is presented.

3.2.1 Input Parameter

For describing the implementation of the mathematical model the input parameter should be explained first. These input parameters are retrieved from the simulation model and could be divided into dynamic and static parameters. This means, a static parameter does not change within the time horizon – in contrast to a dynamic parameter.

Static parameters:

- n different products P_i (i=1,…,n)
- m unrelated parallel machines M_k (k=1,…,m)
- Dedication matrix $D \in \{0,1\}^{n \times m}$. Also $D_k := \{ i \mid D_{i,k} = 1 \}$ is the set of products permitted for processing on machine M_k. In the same manner, $D_i := \{k \mid D_{i,k} = 1\}$ is the set of machines permitted for processing products P_i
- $pt_{i,k} > 0$ is the processing time for a job of product P_i on machine M_k if $D_{i,k} = 1$,
- Machine health value $mh_k \in (0,1]$ $(k = 1,...,m)$ for each machine
- Set of important products $IP \subset \{1,..,n\}$

Dynamic parameters:

- Remaining machine processing time $rpt_k \in \mathbb{N}(k = 1,\ldots,m)$
- Job volume $v_i \in \mathbb{N}(i = 1,\ldots,n)$

Additionally weighting parameters ω_1 and ω_2 exist, which are used to weight the MIP objective function.

3.2.2 Variables

The used decision variables in the mixed integer model are the following:

$X_{i,k} \in \mathbb{N}$	amount of jobs from product P_i assigned to machine M_k (k=1,…m; $i \in D_k$)
$C_{\max} \in \mathbb{N}$	maximum makespan for all machines

With the defined input parameters and variables the created mixed integer model could be described.

3.2.3 Mixed Integer Programming Model

The result from the mathematical model is an assignment of a number of jobs for each product to the machines. Due to the fact that the mathematical model is still a capacity planning model, this is done without knowledge of due dates or release dates. The objective for this MIP model is multi-criteria. On the one hand the maximal makespan $C_{\max}$ has to be minimized and on the other hand the quality Q should be maximized. The quality within the MIP model is equally defined as explained in section 2:

Quality: $$Q = \sum_{\substack{i \in IP \\ k \in D_i}} X_{i,k} \cdot mh_k \tag{1}$$

The optimization model can be formulated as following:

$$\omega_1 \cdot C_{\max} - \omega_2 \cdot Q \rightarrow \min \qquad \text{subject to} \tag{2}$$

$$\sum_{k \in D_i} X_{i,k} = v_i \qquad i \in \{1,...,n\} \tag{3}$$

$$rpt_k + \sum_{i \in D_k} X_{i,k} \cdot pt_{i,k} \leq C_{\max} \qquad k \in \{1, ..., m\} \tag{4}$$

(2) is the objective function. The parameters ω_1 and ω_2 are used to weight the two goals. Typically only one parameter is necessary, but for simplicity ($\omega_1, \omega_2 \in \mathbb{N}$) both parameters are used. (3) is used to ensure that all jobs are assigned to machines. With (4) the makespan $C_{\max}$ is calculated for the whole machine pool. For this the assignment matrix X and the remaining processing times rpt are used.

3.2.4 Result from Mathematical Model and Implementation

The result from this mathematical model is the assignment $X_{i,k}$ of a number of jobs to the machines. This result is directly used within the defined simulation model. For this a user specific script code has been implemented within the simulation model, which is needed to trigger the mathematical optimization run and to transpose the result to the simulation model as shown in Figure 3.

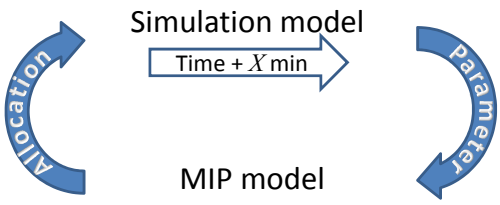

Figure 3: *Dynamic coupling between MIP model and simulation model*

The MIP model is calculated every 10 (simulation) minutes. The MIP model also gets a forecast of 10 minutes for incoming jobs. This means, all jobs with a release date within the next 10 minutes are considered. The implementation of the results within the simulation model is done via product volume lists for each machine. So each machine gets the information, how many jobs of a product are allowed to be processed. The sequencing of the jobs is done by the simulation model using the described ODD rule.

4 Experimental Setup

To test the presented methods, a set of test instances is generated. Table 1 gives an overview of the used parameters.

The unrelated parallel machine work centre consists of 10 machines, processing 20 different products. The number of important products differs between 1 and 4, where the corresponding products are chosen randomly. The maximum machine health is always 1. The minimum health varies between 0.1 and 0.7. The processing times for each product are chosen randomly between one and three hours. The release dates for all jobs are distributed between 0 and 1.03 * minimum makespan. The value "1.03" is calculated experimentally to gain an average flow factor of about three

using the ODD rule. The operational due dates are distributed using the average processing times.

Table 1: *Experimental setup (UD - uniform distribution)*

Factor	Values used	Total values
Number of products n	20	1
Number of jobs per product n_i	UD ~ [100; 500]	1
Number of machines m	10	1
Minimum machine health	0.1; 0.4; 0.7	3
Number of important products	1; 2; 4	3
Product dependent processing times rpt_i	UD ~ [1h; 3h]	1
Release dates rdd	UD ~ $[0, \frac{1.03}{m} \cdot \sum_{i=1,\ldots,n} rpt_i \cdot n_i]$	1
Operational due date odd	$odd = rdd$ + UD ~$[2 \cdot \overline{rpt}; 10 \cdot \overline{rpt}]$	1
	Number of independent instances	50
	Total problems	450

On the basis of these test instances, the presented methods are tested and results are generated.

5 Results

In this section the results for the used methods and the observed objectives are presented. Thereby the parameter ω_2 for the MIP model is chosen out of the set {1; 5; 25; 50}. The parameter ω_1 is 1.

In Figure 4 the results for all test instances and the quality objective are shown.

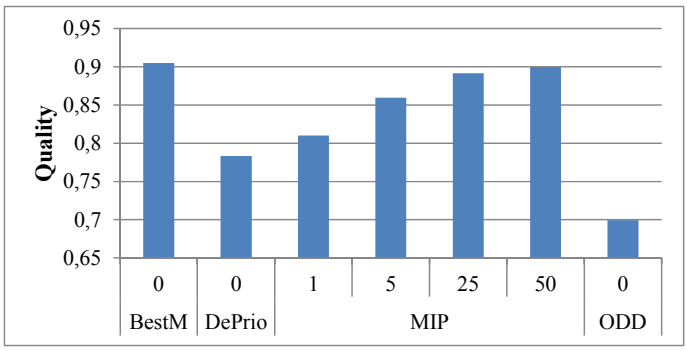

Figure 4: *Result for all test instances regarding quality objective*

Thereby, the x-axis has two rows. The first row describes the parameter ω_2 and the second row the used method. As expected the Best Machine dispatching rule generates the highest quality value. The result of the MIP method depends on the used parameter ω_2. Also, the ODD rule has the lowest quality result.

The results for the tardiness and the flow factor are divided into three bars for each method. The first bar shows the result for all products. In the second bar only the important products are considered and vice versa in the last bar only the result for the normal products are presented.

The tardiness results for all test instances are shown in Figure 5. Thereby the y-axis is cut at 10, because partly results are much higher.

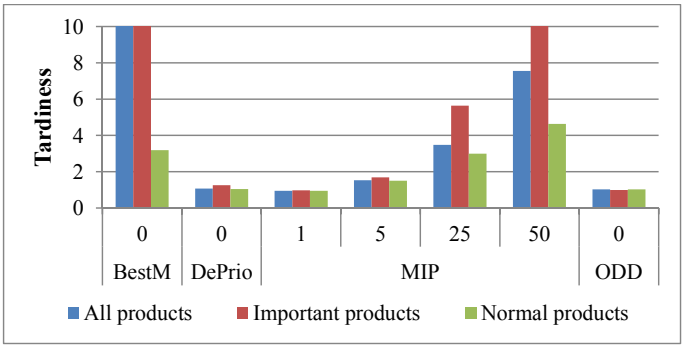

Figure 5: *Result for all test instances regarding tardiness (y-axis cut off)*

As seen in this result, the Best Machine rule and the mixed integer approach with a high parameter ω_2 generates poor results regarding tardiness. This is due to the reduced dedication matrix especially for these test instances with a high number of important products. The DePrio rule performs a little bit poorer than the ODD rule for important products. This rule could also be parameterized. However, this has not been investigated until now. To show the influence of the number of important products, in Figure 6 and Figure 7 the results for one and four important products are presented. Thereby, this time the y-axis is not cut off. This result shows that the choice of parameters is important.

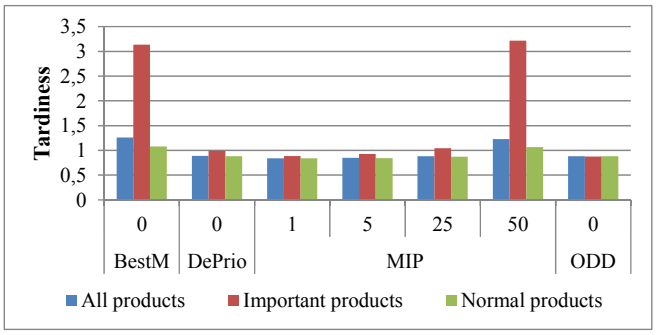

Figure 6: *Results for tardiness for one important product*

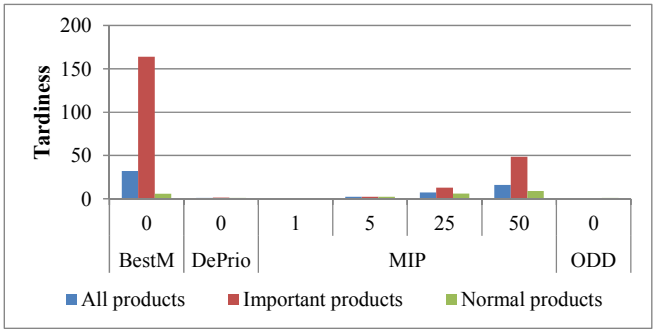

Figure 7: *Results for tardiness for four important products*

The last investigated objective is the flow factor. The results are shown in Figure 8.

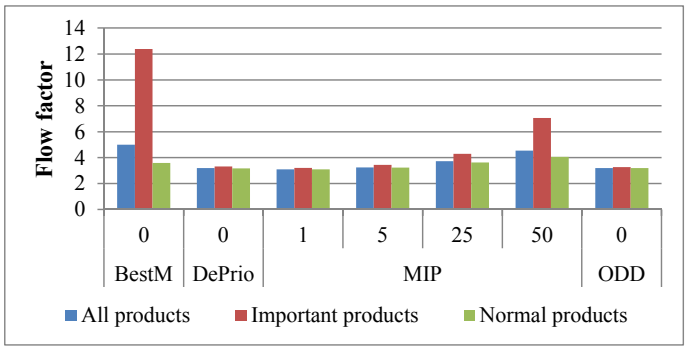

Figure 8: *Result regarding the flow factor for all test instances*

Here a similar result as seen for tardiness could be estimated. Also the minimum health values for the machines have an influence on the results. So in Figure 9 the result for a minimum health value of 0.7 is shown.

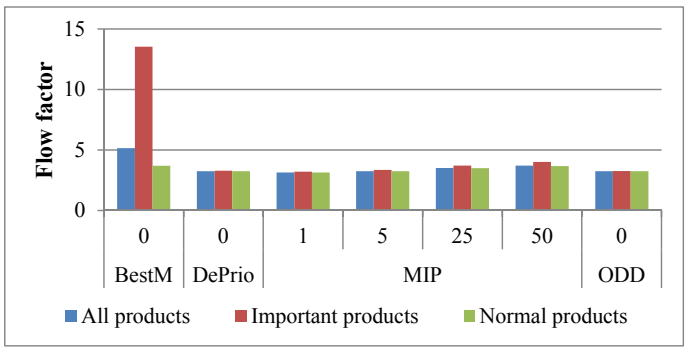

Figure 9: *Result for flow factor and a minimum machine health of 0.7*

Here the deviation of flow factor is much smaller than in Figure 8. This can be explained by the objective function of the MIP model. In the case where the deviation of the minimum health is smaller, also the possible optimization for quality objective is smaller and so the influence of parameter ω_2 drops.

6 Conclusion and Outlook

In this paper a yield integrated scheduling method, which uses machine health parameters, is implemented. For this, different dispatching rules and a mixed integer programming model are compared with the well-known ODD dispatching rule. The results show that the mathematical approach gains slightly better results compared to the practical dispatching rule. Further, an improvement in the quality often concludes to a worsening of other objectives. The results in our study show an improvement in quality by an average of up to 20% compared to the ODD rule. Here, the formulation used for the quality objective is just an abstract improvement of the yield. The result cannot be directly converted into yield. This has to be done for each problem area specifically. Overall, the presented investigation is a proof of concept for implementing machine health parameter to scheduling methods.

Further research regarding the parameterization of the practical dispatching rule and the mathematical approach should be performed. Also more complex test instances as well as real data should be used to get a better overview of possible improvement.

Acknowledgement

The work has been performed in the project eRamp (Grant Agreement N°621270), co-funded by grants from Austria, Germany, Slovakia and the ENIAC Joint Undertaking.

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