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SIMULATION-BASED OPTIMIZATION FOR SOLVING A HYBRID FLOW SHOP SCHEDULING PROBLEM

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ABSTRACT

This paper describes the solution of a hybrid flow shop (HFS) scheduling problem of a printed circuit board assembly. The production comprises four surface-mount device placement machines on the first stage and five automated optical inspection machines on the second stage. The objective is to minimize the makespan and the total tardiness. The paper compares three approaches to solve the HFS scheduling problem: an integrated simulation-based optimization algorithm (ISBO) developed by the authors and two metaheuristics, simulated annealing and tabu search. All approaches lead to an improvement in terms of producing more jobs on time while minimizing the makespan compared to the decision rules used so far in the analyzed company. The ISBO delivers results much faster than the two metaheuristics. The two metaheuristics lead to slightly better results than the ISBO in terms of total tardiness.

1 INTRODUCTION

This paper describes the solution of a hybrid flow shop (HFS) scheduling problem with major and minor sequence-dependent setup times based on an industrial case of a printed circuit board (PCB) assembly. The objective was to minimize the makespan and the total tardiness. An HFS production environment consists of s production stages in series. Each production stage comprises m identical parallel machines. Each job j has to be processed on each production stage on one of the identical machines (Pinedo 2012). This problem is NP-hard (Lenstra et al. 1977). The paper proposes three different solutions to this HFS problem: an integrated simulation-based optimization algorithm (ISBO) developed by the authors and two widely used metaheuristics, simulated annealing and tabu search.

Scheduling is the deployment of resources in order to complete a set of tasks during a determined time span (Baker and Trietsch 2009). Scheduling problems have been extensively investigated in different fields of academia due to its essential role in manufacturing environments and different service sectors (Ruiz and Vázquez-Rodríguez 2010). Efficient allocation of resources supported by the appropriate sequencing is considered to be a major mathematical optimization problem (Lenstra et al. 1977). Johnson (1954) presented an optimal schedule for the two machine flow shop with sequence-dependent setup times, which is not as complex as an HFS problem. Direct optimization approaches have been previously implemented to solve HFS problems. Wittrock (1990) adopted a branch and bound algorithm to address the problem of identical parallel machines with major and minor sequence-dependent setup times, which can be considered as a simplified form of an HFS, and reported a near optimal solution. The branch and bound approach requires long computational time, even for small instances. Dynamic programming represents another direct optimization approach, which can be applied to solve HFS problems divided into smaller sub-problems (Baker and Trietsch 2009). The recursive behavior of a dynamic programming approach facilitates the investigation of the whole solution space of a moderate size problem in reasonable computational time (Pinedo 2012).

Heuristics are used to obtain good solutions in reasonable computational timen when the problem domain gets more complex (Allaoui and Artiba 2004). Priority Dispatching Rules (PDRs) are widely used in practice to define scheduling policies in manufacturing environments. PDRs are the simplest form of heuristics due to their ease of use and intuitive nature (Andersson et al. 2008). Shortest Production Time (SPT) and Earliest Due Date (EDD) are typical PDRs. They are often implemented to solve problems with a single objective function and they lack on solution quality as soon as the objective function gets more complex (Andersson et al. 2008). More sophisticated heuristics are adopted to deal with HFS scheduling problems. Voß (1993) and Gupta (1988) used heuristics based on local search algorithms to solve a special case of an HFS with exactly one machine on the second stage and with the objective to minimize the makespan. This problem is still NP-hard (Gupta 1988). Local search algorithms are improvement procedures based on an initial feasible solution for the problem. They recursively search in the neighborhood of the initial solution for a better solution until a terminating condition is met.

Metaheuristics are often used to solve scheduling problems and are a powerful solution approach. Metaheuristics are guided local search algorithms. They are based on local search improvement algorithms and a general optimization or control strategy. The control strategy is used to guide the local search algorithms (Voudouris and Tsang 2003). The idea of metaheuristics is motivated by the fact that a local search algorithm often only obtains a local optimum from the solution space (Ross 2005). Simulated Annealing (Allaoui and Artiba 2004; Mirsanei et al. 2011) and Tabu Search (Wang and Tang 2009) are widely used metaheuristics.

2 SYSTEM DESCRIPTION AND PROBLEM FORMULATION

Any scheduling problem can be described and classified based on the machine environment and configuration, the job characteristics and the objective function (Graham et al. 1979).

2.1 Machine Environment and Configuration

The analyzed production system is a hybrid flow shop, which consists of two production stages (see Figure 1). The first production stage comprises four identical parallel surface mount device (SMD) placement machines, which are usually the critical resources in the observed production system (Csaszar et al. 2000). Consequently, the analysis was focused on the SMD placement machines. The second production stage consists of five identical parallel automated optical inspection (AOI) machines. Each job j has to be processed on each production stage s on one of the identical machines m.

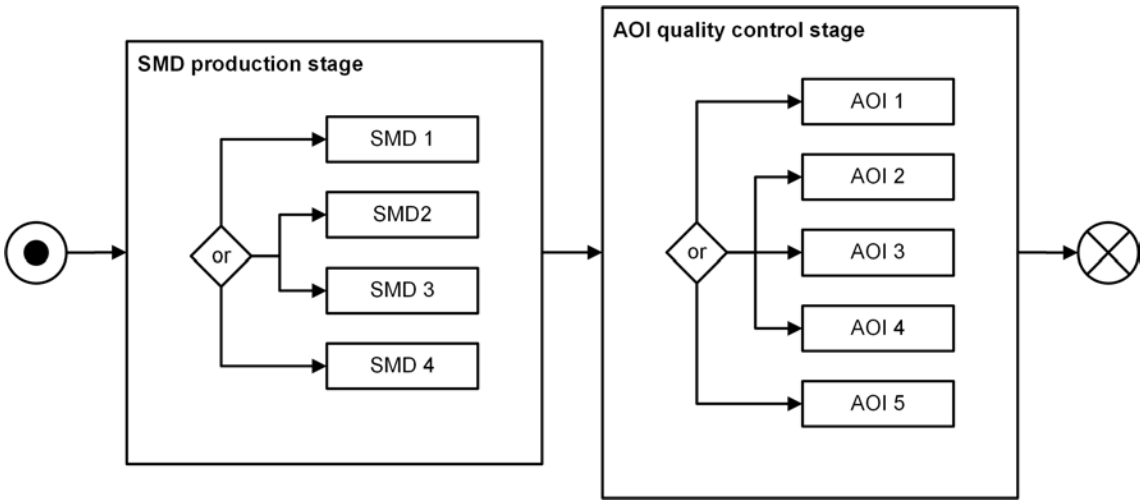

Figure 1: Two stages hybrid flow shop.

2.2 Job Characteristics

Jobs of the analyzed HFS scheduling problem have the following characteristics:

- The number of jobs in a certain time period and the number of products per job are known and fixed.
- Part types are very heterogeneous.
- The family type of a job depends on the used raw materials.
- The processing time of each job on a certain machine and production stage is known and fixed.
- The priority of a job represents its desired delivery date.
- The sequence-dependent setup time is the time to setup the machine when changing jobs.
- Machine breakdowns are modelled indirectly through reduced available machine time.
- The buffer size between production stages is unlimited.

On the first production stage (SMD), jobs are scheduled with sequence-dependent major and minor setup times. On the second production stage (AOI), jobs are scheduled with sequence-independent setup times. Wittrock (1990) as well as by So (1990) introduced the concept of major and minor setup time to describe sequence-dependency. Jobs which share common raw materials are grouped into product families. The setup within a product family leads to a minor setup time. Whereas the setup between two different product families induces a major setup time. On the first production stage job splitting is not permitted, which means that a job's production process cannot be stopped to produce a different job due. Job splitting is allowed on the second production stage.

2.3 Objective Functions

Accomplishing a balance between production system efficiency and the job's due-date is a trade-off decision. For this reason, tardiness has been frequently used as a major supplementary performance criterion along with the makespan (Lenstra et al. 1977). The objective functions of the analyzed HFS problem are to minimize the makespan C_{max} (1) and the total tardiness T (2). The makespan is the necessary time to complete all released jobs (Wittrock 1990). To minimize the makespan it is important to minimize the number of major setups. Tardiness is the difference between the completion time of a job C_j and its due date d_j as shown in (2).

$$C_{\max} = \max C_j \ \forall \ j = 1, \ ..., \ n \tag{1}$$

$$T = \sum_{j=1}^{n} T_j, \ T_j = \max \ (C_j - d_j, \ 0) \tag{2}$$

3 SOLUTION APPROACHES AND IMPLEMENTATION

The problem to minimize the makespan of a two stage hybrid flow shop is NP-hard (Gupta 1988). The development of a polynomial algorithm, which can provide an optimal solution in a reasonable time, is unlikely possible. Thus, breaking down the problem could be the key to obtain a near optimal solution by solving smaller sub-problems. It is often easier to solve the allocation and the sequencing independently (Baker and Trietsch 2009). Initially, jobs are allocated to the machines on each production stage. Four single machine problems with sequence-dependent setup times emerge on the first production stage and five single machine problems with sequence-independent setup times arise on the second production stage. A heuristic and metaheuristics were used to solve the allocation problem. A dynamic programming approach was used to develop a sequencing algorithm that builds a near optimal sequence of jobs on each machine.

The first solution strategy presented is an integrated simulation based optimization (ISBO). The ISBO integrates a heuristic and a sequencing algorithm into a simulation model. The second and the third approach use a metaheuristic: simulated annealing and tabu search. Both metaheuristics are combined with a sequencing algorithm. A simulation model was used to assess the quality of the metaheuristics' solutions.

3.1 Integrated Simulation based Optimization

In the integrated simulation Based Optimization (ISBO) (see Figure 2), the simulation is a part of the solution rather than an evaluation method for it. The allocation and sequencing algorithms are integrated in the simulation model. The simulation model was built with ExtendSim 9. The discrete-rate and discrete-event simulation-libraries were used to implement a hybrid mesoscopic simulation approach to avoid a long computation time (Reggelin and Tolujew 2011). The SMD and AOI production processes are modelled using the discrete-rate library. Flow rates differ depending on the current part type, being produced by the machines. The dispatching and decision making processes are modelled using the discrete-event library in order to ensure a high level of accuracy. The flow of a job is changed to a single object at decision points. When a job is released for processing, it is again modelled with a flow rate.

Product families and their jobs are initially allocated to the machines before the simulation starts. The shortest process time (SPT) rule determines the initial allocation of the product families on the first production stage SMD. The earliest due date (EED) rule initially allocates the jobs on the second production stage AOI. During the simulation, the interaction between the allocation and the sequencing algorithm leads to a sustainable production strategy with a near optimal sequence being continuously generated on each machine. The allocation algorithm ensure a balance of the production load between the machines.

In order to minimize the makespan, all jobs of a product family should ideally be manufactured successively on the same SMD machine to avoid major setups. However, this would lead to delivery time violations of many jobs. The sequencing algorithm operates on two levels, the product family level and the job level (see Figure 3). On the family level, the smallest family which contains at least one of the highest job priorities is chosen. Then, the sequencing algorithm switches to the job level. On the job level, the algorithm tends to choose jobs from the same family according to the priority of jobs using the EDD rule. The sequencing algorithm keeps operating on the job level until jobs of the family are completely produced or a critical point is met. The critical point describes a situation, when it is no longer possible to produce a job from the same product family without violating the delivery date of other jobs from different families. Choosing the smallest family increases the chance that the chosen family is completely produced before reaching a critical point. This behavior avoids a later major setup.

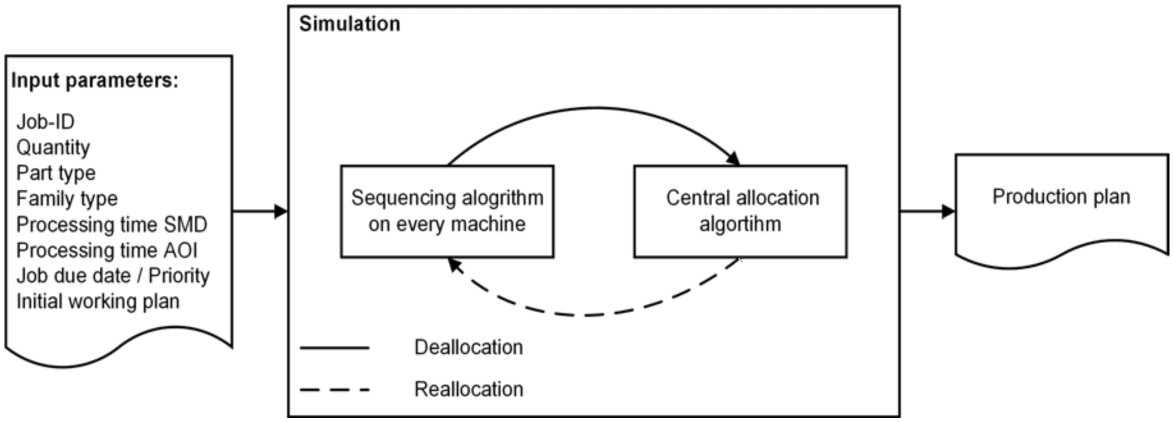

Figure 2: Integrated Simulation Based Optimization.

The allocation algorithm tries to sustain a balance of the production load between the machines on each production stage. It performs two types of allocation, event-based allocation and pre-defined allocation. The event-based allocation is triggered by the sequencing algorithm (see Figure 2 and Figure 3) when critical points are reached. It checks for the least loaded machine and reallocates the remaining jobs of the family to this machine. The pre-defined allocation is performed each day to balance the production load of the next highest three priorities. All families except the one in production are deallocated. The allocation algorithm starts reallocating families to the least loaded machines during the next three simulated working days. It tends to balance the amount of must-be-produced jobs in the next three days according to their delivery date between the machines. The pre-defined allocation processes tries to avoid major setups by sustaining a balance of the must-be-produced jobs between the machines by avoiding critical points. Manipulating the allocation of families during the simulation better explores the solution space of the problem after significant changes in the production load. Producing from different families changes the form of the production load and therefore, finding an enhancement in the allocation is possible during the simulation despite a perfect initial allocation.

3.2 Simulated Annealing

Simulated annealing was combined with a discrete-event simulation model to solve the allocation. For the sequencing, the algorithm shown in Figure 3 was used again. Simulated annealing is derived from the concept of physical annealing of a solid substance. It was first introduced in the early eighties by Kirkpatrick et al. (1983) to solve combinatorial optimization problems. Annealing is the process of melting a solid substance and cooling it slowly down until the particles arrange themselves in the solid state (Aarts et al. 2005; Kirkpatrick et al. 1983; Mirsanei et al. 2011). When the temperature is high the particles are free to move randomly since they hold a high energy. In this state, the simulated annealing shows a very random behavior and is more likely to accept a worse solution than the current best solution (Mirsanei et al. 2011). When the cooling process starts, the solid state reduces the random behavior of the simulated annealing. The algorithm starts to search for a better solution in the same region of the solution space, rather than jumping from one region to another region.

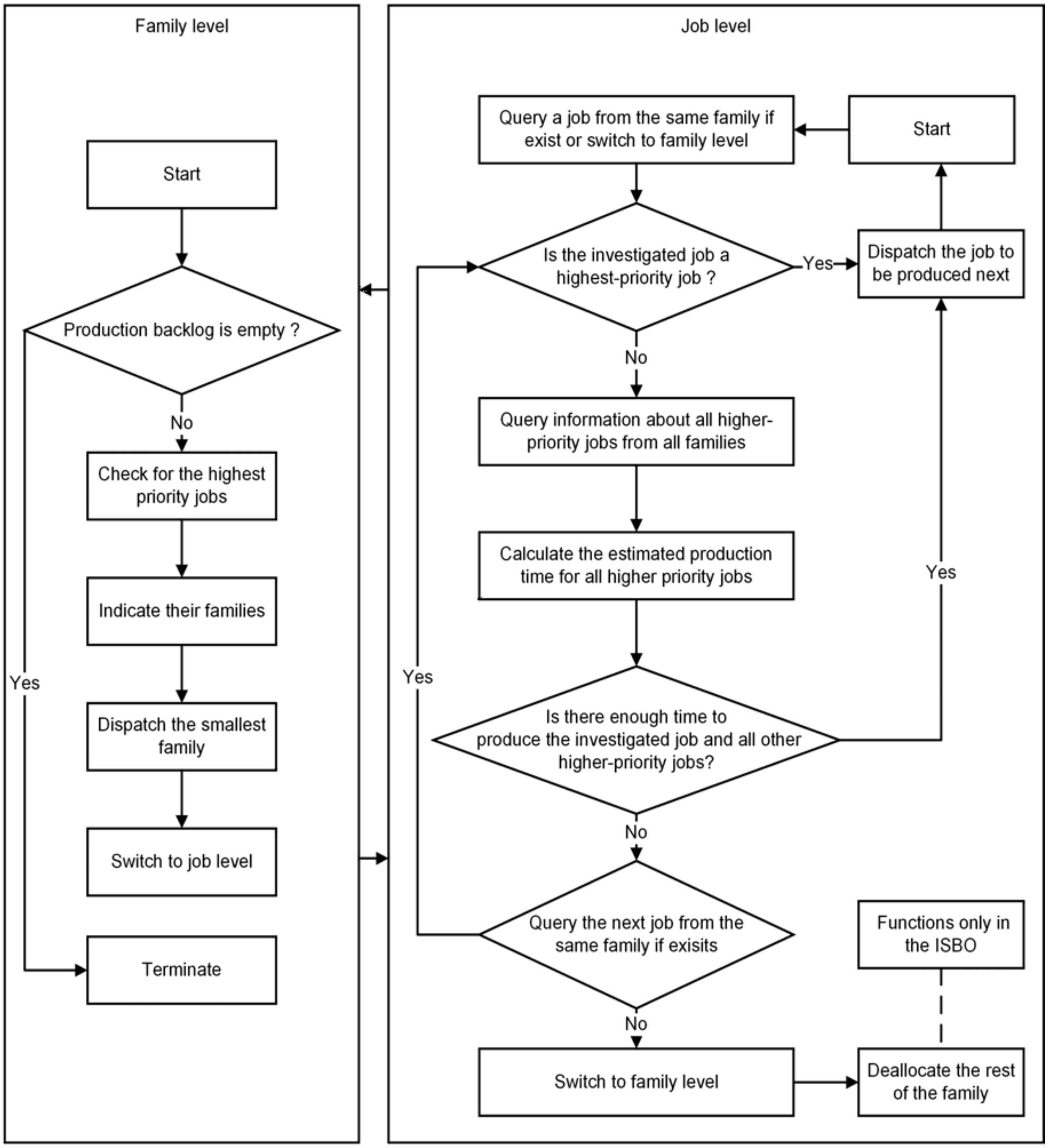

Figure 3: Sequencing Algorithm.

Simulated annealing is used to solve the allocation problem on the SMD placement machines. The approach starts with a feasible solution to the problem as depicted in Figure 4. Then, the neighborhood search of the simulated annealing tends to find randomly a better solution in the current region of the solution space. The neighborhood search is based on a random single point operator (Naderi et al. 2009), in which a random family is picked and reallocated randomly to a different SMD placement machine. The number of changes (number of reallocated families) was restricted to one to avoid the simulated annealing behaving like a random search. After all families being allocated, the sequencing algorithm starts to build the production schedule of each SMD placement machine. After that, the jobs are allocated to the AOI machines based on their expected finishing time on the SMD placement machines. The allocation to the

AOI machines tries to achieve a balanced production load between the machines and tries to consider the priorities of the jobs (due dates). The generated schedule is evaluated by using the discrete-event simulation model. The production sequences on the AOI machines are determined with the help of the EDD rule during the simulation run.

After passing the result of the simulation run back to the simulated annealing algorithm, three cases can be differentiated:

1. The new schedule dominates the old one in both objective values. The solution is accepted and used as the next start solution.
2. The old schedule dominates the new one.
3. Neither the old schedule nor the new one dominates.

For case two and case three, the Boltzmann distribution is used to decide whether to accept a new solution or not (Naderi et al. 2009). A weighted sum of the observed objective values was used since the Boltzmann distribution contains only one value. The probability of accepting a worse solution depends on the current temperature of the simulated annealing. The setup of the parameters of the simulated annealing strongly impacts its quality (Pirlot 1996). The parameters are initial temperature, the number of iterations before changing the temperature and the cooling rate. In this implementation, the simulated annealing starts with an initial temperature between 20 and 30 degrees. Each temperature contains 10 to 20 iterations. The implemented cooling schedule is linear and the cooling rate deviates between 0.1 and 0.25 degrees.

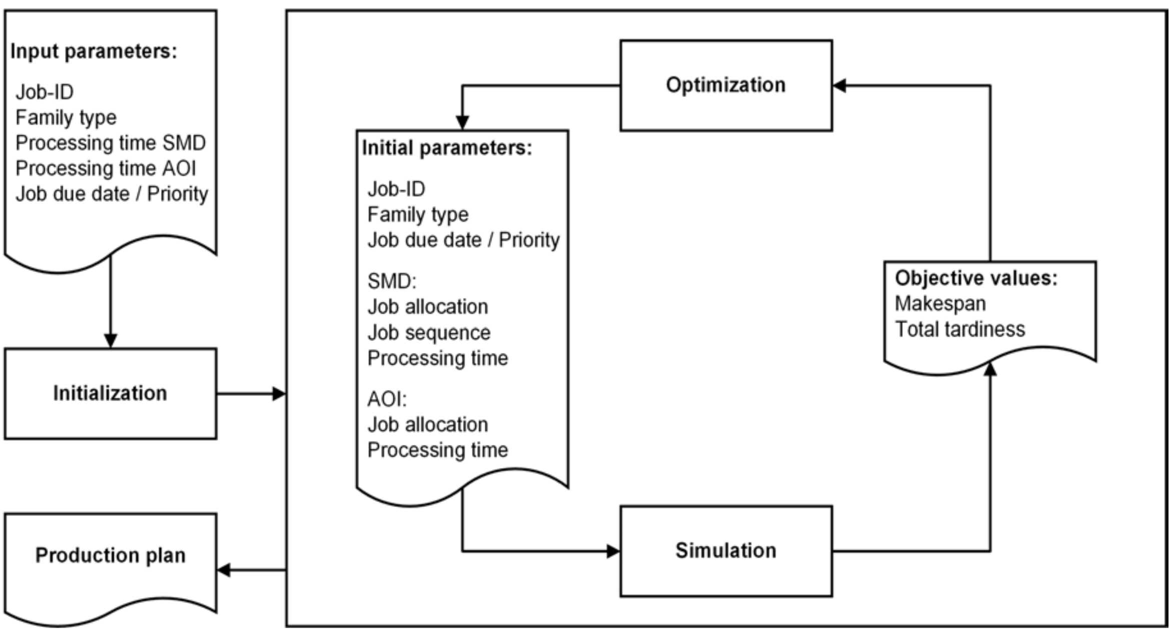

Figure 4: Metaheuristic approach.

3.3 Tabu Search

The tabu search algorithm was combined with the same discrete-event simulation model, which was used for the simulated annealing. For the sequencing, the algorithm shown in Figure 3 was used again. Tabu search is one of the oldest metaheuristic approaches, which was introduced by Glover (1986) to solve combinatorial optimization problems. In contrast to simulated annealing, tabu search is based on a deterministic solution mechanism, in which the neighborhood of the initial solution is build based on a set of specific moves, which are conducted on the initial solution to obtain new solutions. The current neighborhood is then investigated to identify the best solution. The initial solution is replaced by the best solution found, before starting the next iteration. The move which led to the current solution is stored in the tabu list. The aspiration function of the tabu search is used independently to evaluate the quality of the generated solutions of the moves from the tabu list (Nowicki and Smutnicki 1996).

The implementation of the tabu search in this paper is based on a single point operator neighborhood search. A single move is committed by picking a family and reallocating it to another machine. Each family is associated with three moves that generate three different solutions in the neighborhood. The solutions represent the possible allocations of each family to all considered SMD placement machines. For each generated new allocation, the sequencing algorithm is used to build the new production schedule on each SMD placement machine. Then, the jobs are allocated to the AOI machines, based on their expected finishing times on the SMD placement machines. Finally, the quality of each production schedule is evaluated using simulation. The results of the simulation runs are stored to identify the best solution and add its SMD allocation to the tabu list. The length of the tabu list is limited either to 10 or 15 solutions. Since two objective functions (makespan, tardiness) are considered, a weighted sum was used to identify the best solution before starting the next iteration. The forbidden schedules from the tabu list are evaluated using the aspiration function. If a dominant solution is found, it is used to start a new iteration.

4 COMPUTATIONAL RESULTS

The experiments were performed on four different real datasets. The datasets are heterogeneous in terms of the number of product families, the number of jobs and their associated part types as shown in Table 1. The major setup time averages 65 minutes and the minor setup time 20 minutes.

Table 1: Input datasets.

	Dataset 1	**Dataset 2**	**Dataset 3**	**Dataset 4**
Number of jobs	164	170	175	143
Number of families	41	37	36	35
SMD processing time per job (min)	4 - 3,142	2 - 3,736	4 - 3,293	4 - 3,209
Accumulated SMD processing time (min)	54,685	62,345	61,274	56,250
AOI processing time per job (min)	4 - 4,351	3 - 5,590	5 - 3,528	3 - 4,300
Accumulated AOI processing time (min)	72,528	88,702	74,738	79,294
Quantity of parts (PCBs) per job	40 - 109,920	20 - 143,040	21 - 186,960	20 - 216,000

Table 2 shows the computational results of the approaches used to solve the HFS problem. The family production (FP) scenario is a batch production strategy, which has been used so far by the company to determine the scheduling policies for their production. In the FP, a machine, producing jobs from a family, is not allowed to be switched to another family until the current family is completely produced. This strategy leads to a minimum number of major setups and many jobs being late. The standard priority dispatching rules (SPT and EDD) lead to bad results in terms of generating many major setups and for the SPT also in terms of many jobs being late.

The integrated simulation based optimization (ISBO), the simulated annealing (SA) and the tabu search (TS) show significant improvements in terms of makespan and total tardiness in comparison to the scheduling policies used in the company. The ISBO slightly outperforms the simulated annealing and tabu search in terms of the makespan. This is caused by the dynamic behavior of the allocation algorithm implemented in the ISBO, which tends to balance the critical jobs and their families instantly during the simulation. Simulated annealing and tabu search show a similar behavior for the analyzed problem.

Table 2: Computational results of the different solution approaches.

	Makespan (minutes)	**Major-Setups (number)**	**Penalty (number)**	**Average Tardiness (minutes)**
Dataset 1				
FP	23,513	37	39	5,097
SPT	23,586	126	30	2,883
EDD	21,154	104	0	0
ISBO	19,354	43	1	148
SA	21,930	45	0	0
TS	19,669	45	0	0
Dataset 2				
FP	25,447	33	52	5,225
SPT	26,662	135	31	4,811
EDD	26,226	136	9	537
ISBO	21,819	53	0	0
SA	23,108	55	0	0
TS	25,142	55	0	0
Dataset 3				
FP	23,626	32	62	5,060
SPT	25,756	131	36	4,143
EDD	22,603	139	8	750
ISBO	19,979	56	2	268
SA	23,059	59	0	0
TS	22,507	60	0	0
Dataset 4				
FP	23,539	31	48	5,362
SPT	20,507	113	26	4,430
EDD	21,145	113	2	482
ISBO	18,806	42	3	213
SA	20,562	58	0	0
TS	21,610	57	0	0

The results from the ISBO were obtained from a single simulation run, which took approximately 30 seconds computation time. The simulated annealing was configured to have 1,500 simulation runs and delivered results after approximately 3 hours computation time. The tabu search was configured to run between 20 and 30 iterations, which corresponds to about 2,100 and 3,150 simulation runs. The number of simulation runs in the tabu search depends on the number of product families in the dataset. The experiments were conducted on a computer with the following characteristics: CPU 4 x 2.6 GHz, RAM 8 GB and windows operating system.

5 CONCLUSION

Three applied solution approaches integrated simulation-based optimization (ISBO), simulated annealing and tabu search solved the hybrid flow shop (HFS) scheduling problem better than the decision rules used very often in practice in the printed circuit board assembly. All three solution approaches led to an improvement in terms of minimizing the makespan and producing more jobs on time. The ISBO delivers results much faster than the two metaheuristics. The metaheuristics lead to slightly better results in terms of total tardiness. The dynamic allocation used in the ISBO allows for a very deep investigation of the solution space during the simulation. This leads to very good results in terms of minimizing the makespan compared to the two metaheuristics. The experiments with four real data sets have revealed one major challenge of solving HFS problems: large jobs can lead to difficulties in finding a good solution.

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