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Applications

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Process planning and scheduling optimisation with alternative recipes

Optimierung der Prozessplanung und -vorbereitung durch alternative Rezepte

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Abstract: This paper considers an application of a new variant of a multi-objective flexible job-shop scheduling problem, featuring multisubset selection of manufactured recipes, to a real-world chemical plant. The problem is optimised using a multi-objective genetic algorithm with customised mutation and elitism operators that minimises both the total production time and the produced commodity surplus. The algorithm evaluation is performed with both random and historic manufacturing orders. The latter demonstrated that the proposed system can lead to more than 10 % makespan improvements in comparison with human operators.

Keywords: multi-objective job-shop scheduling, process manufacturing optimisation, multi-objective genetic algorithms

Zusammenfassung: Dieser Artikel beschreibt die Anwendung einer neuen Variante eines mehrdimensionalen Optimierungsproblems in der flexiblen Fertigungsplanung mit mehreren Teilmengen von Fertigungsrezepten in einer realen Fabrik zur Herstellung von Farben. Das Problem wird mithilfe eines mehrdimensionalen genetischen Algorithmus mit angepassten Mutations- und Elitismus-Operatoren optimiert. Dieser Algorithmus minimiert sowohl die Gesamtproduktionszeit als auch den produzierten Warenüberschuss. Die Bewertung des Algorithmus wird sowohl mit zufällig generierten als auch mit realen historischen Fertigungsaufträgen durchgeführt. Letztere haben gezeigt, dass das vorgeschlagene System im Vergleich zum menschlichen Bediener zu einer Verbesserung der Produktionsdauer um mehr als 10 % führen kann.

Schlagwörter: mehrdimensionale Fertigungsplanung, Fertigungsoptimierung, mehrdimensionale genetische Algorithmen

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1 Introduction

Manufacturing processes' scheduling is often modelled using Job-shop Scheduling Problem (JSP), an optimisation problem whose purpose is to determine allocation of manufacturing jobs to the available resources at particular times to optimise certain key objectives, for example, the total manufacturing time aka makespan [7]. Due to its practical applications, the research related to JSP has been conducted by numerous researchers [1] and assorted variants of this problem have been introduced to describe real-world scenarios. Some examples of them are Flexible Job-shop Scheduling Problem (FJSP), where each job can be processed on any machine, FJSP with process plan flexibility (FJSP-PPF) [12] or JSP with alternative process plans [13]. Recently, a multi-objective Flexible Job-Shop Scheduling Problem with Alternative Recipes (FJSPAR) has been introduced in [4]. In FJSPAR, each bulk commodity can be produced in various quantities using different recipes with different manufacturing time, energy consumption etc. The recipes can have different resource affinities, i.e., they can be executed on certain classes of resources only. The objectives are to minimise the makespan and produce the commodities in the amounts as close to the ordered ones as possible, i.e., to minimise the discrepancies between the ordered and the manufactured quantities for each commodity. FJSPAR not only schedules the jobs but also selects the multisubset (i.e., a combination with rep-

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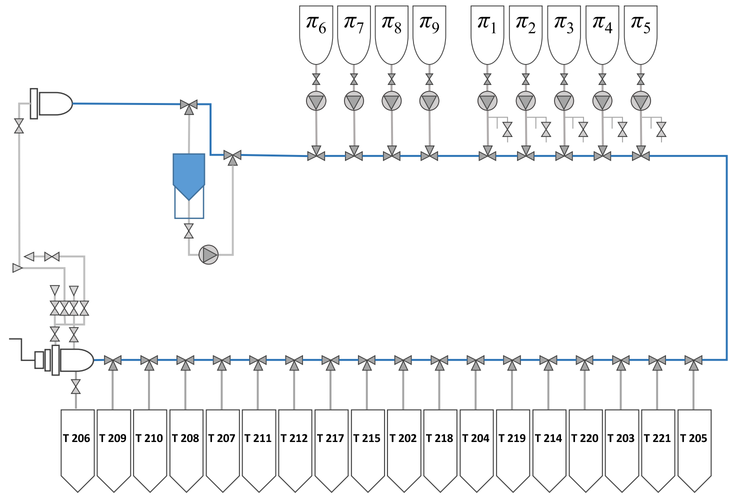

Figure 1: An example chemical plant architecture.

etitions) of the recipes to be manufactured. Hence, FJSPAR integrates both the process planning and scheduling.

The introduction of FJSPAR has been motivated with a real-world manufacturing process for mixing/dispersion of powdery, liquid and paste components, following a stored recipe in a chemical plant whose architecture is similar to the one presented in Fig. 1. In this figure, each resource $\pi_k, k \in \{1, \dots, 9\}$ represents a production line whose main component is a mixer. The mixers vary for their size and processing time and hence need various recipes. Four types of white paints can be produced in the factory and each mixer can be used to produce any commodity. The amount of paint produced during one manufacturing process and processing time vary depending on the mixer type and paint type and there is a unique recipe for each combination of mixer type and paint type. The storage tanks, shown at the bottom of the figure, are connected with the mixers via pipelines. They limit the amount of the paints that can be produced as they have limited capacity. Hence, the considered FJSPAR instance has the objectives related to minimisation both the total manufacturing time and the amount of produced paint as long as they satisfy the order.

This paper is complementary to the previous paper of the authors [4]. That paper proposed a new variant of a multi-objective flexible job shop scheduling problem featuring multisubset selection of manufactured recipes, a novel associated chromosome encoding and customisation of the classic MOEA/D multi-objective genetic algorithm with new genetic operators. This paper focuses more on the application side of this research. For technical details regarding the algorithmic issues related to the proposed technique, a reader is referred to the above-mentioned paper.

2 Related work

As manufacturing resource scheduling is an instance of NP-hard problems [5], it is difficult to be solved exactly in practice and hence various heuristics have been applied. Since such scheduling often requires optimisation concerning more than one criterion, multi- or even many-objective heuristics have been employed. Among them, genetic algorithms (GAs) have been gained popularity since a seminal paper by Ishibuchi and Murata [9]. In that paper, non-dominated[1] solutions have been sought for makespan, total flowtime, mean tardiness. The quality of each candidate solution has been assessed with its fitness value being a weighted sum of these three criteria. In that paper, the weight values were chosen randomly upon selection of the parent individuals. Consequently, a solution space has been created with each solution generated according to a unique weight vector. Then, the solutions have been improved during a local search process. That approach has been applied to a classic JSP with limited plant size and taskset cardinality and hence it is rather difficult to apply that approach to a real-world factory. The approach described in this paper applies to more realistic scenarios and employs the more recent multi-objective genetic algorithm MOAE/D [14], which benefits from the idea of generating various solutions from objective weighted sums as introduced in [9].

Several real-world scheduling problems have been deeply researched, typically being solved by customised

1 A solution s is said to be non-dominated if s has a better value than any other found solutions for at least one objective.

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multi-objective GAs. For example, in [10], a real-world manufacturing problem originating from a steel tube production has been described by extending the classic FJSP and solved using a multi-objective GA with two objectives, namely reduction of the idle time on machines and waiting time of orders. The authors of that paper stressed that it was virtually impossible to apply the earlier research works on JSP in practice as they were based on overly simplified models and assumptions. In that paper, the production routes depend on the orders and each production stage could be processed on various homogeneous machines. The model proposed in that paper can be used in numerous job production problems, but is inappropriate in the case of batch manufacturing. In particular, it does not consider recipe selection or minimisation of the commodity surplus, which is addressed by the model described in this paper. Readers can refer to the survey presented in [11] to appreciate the complexity of the batch manufacturing in general. The factory model introduced in this paper is capable of describing the majority of the features from the general batch scheduling classification presented in [11], including the "sequence-depending setup", in which sequences of two manufacturing jobs scheduled to be processed subsequently by the same machine can require a time gap of a certain length between them (corresponding to e. g., cleaning the machine in a physical plant).

An interesting real-world problem related to textile batch dyeing scheduling has been described in [8]. Similarly to the problem presented in this paper, both the temporal features and the weight of the products are considered. In the textile dying industry, cloths of the same colour can be batched together as long as their total weight does not surpass the capacity of the manufacturing resource. However, for the problem addressed in this paper, the resources are capable of producing only an exact weight of a given commodity, not lower or higher, and the total amount of a manufactured commodity is only influenced with the selection of the recipes' multisubset to be executed. Instead of a batching heuristics, a method for recipe multisubset selection that optimises a set of criteria would be desirable.

Gen and Lin have surveyed several multi-objective GAs applied to manufacture scheduling problems in [6]. These problems have been modelled as a classic JSP, FJSP, dispatching in a flexible manufacturing system (FMS) and integrated process planning and scheduling (IPPS). The real-word scenario used in this paper is consistent with several realistic assumptions in those problems, including alternative resources with assorted efficiency as in FJSP. For storage facilitation as in FMS. The manufacturing planning and scheduling are performed together, similarly to IPPS. Yet, none of those problems included a selection of a multisubset of recipes for producing the same commodity nor addressed the problem of minimising commodity surplus. Both these features are essential to the real-world scenario given in this paper. The surplus minimisation has not been mentioned in a survey of objective functions used for multi-objective FJPs [2].

3 Problem formulation

The considered extended version of traditional FJSP consists of assigning a multisubset (i. e., a combination with repetitions) of manufacturing recipes γ_j, $j = 1, \ldots, n$ to factory resources $\pi_i \in \Pi$, $i = 1, \ldots, m$ at particular times. Not all resources are capable of executing each recipe; the subset of resources compatible with recipe γ_j is denoted as Λ_j. Execution of recipe γ_j on any compatible resources produces u_j units of commodity δ_l, $l = 1, \ldots, r$ during $t_{i,j}$ units of time. By executing a selected multisubset of recipes, θ_l units of commodity δ_l is manufactured. This amount needs to be higher or equal to o_l units, as specified in order O. The surplus of commodity δ_l is the difference between its produced and ordered amounts, $\sigma_l = \theta_l - o_l$. A particular instance of recipe γ_j in the recipe multisubset is denoted as $\gamma_{j,k}$, $k = 1, \ldots, \mu_j$, where $\mu_j = \lceil o_l / u_j \rceil$ is the minimal number of recipe instances that satisfies the ordered amount of δ_l. Hence, the cardinality of the considered recipe multisubset is upper-bounded with $\eta = \sum_{j=1}^{n} \mu_j$. If two recipe instances γ_{j_1,k_1} and γ_{j_2,k_2} manufacturing different commodities are scheduled to be processed by the same resource one after another, a certain time gap between them may be required (corresponding e. g., to resource reconfiguration or cleaning in real plants). Hence, the instance ordering can influence the makespan. This ordering is defined with priority $p_{j,k} \in \mathbb{N}_0$ of each recipe instance $\gamma_{j,k}$, where 0 denotes the highest priority. The scheduling is performed according to the priority non-preemptive policy.

4 Genetic algorithm customisation

The multiobjective evolutionary algorithm based on decomposition (MOEA/D) proposed in [14] is an efficient approach when more than three objectives need to be optimised simultaneously, as in the considered FJSPAR (one makespan and a number of commodity surpluses).

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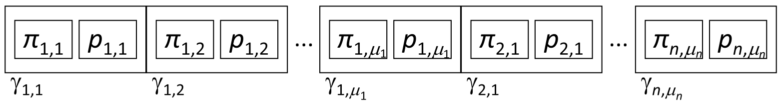

Figure 2: Chromosome encoding for manufacturing processes with alternative recipes.

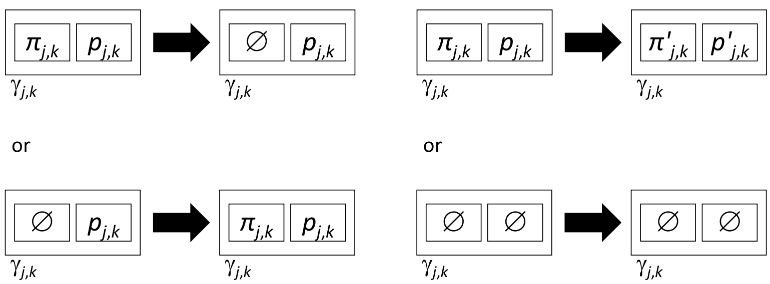

Figure 3: Two customised mutation operators.

MOEA/D decomposes a multiobjective optimisation problem into a set of different single-objective optimisation subproblems, each with different objective weights. These objective weights may be, for example, spread uniformly in the weight space. As in any genetic algorithm, the solutions are encoded in a form of so-called chromosomes composed with a number of genes. In the proposed approach, each chromosome includes 2η elements (genes): the odd elements store the resource indices that the corresponding recipe instances have been allocated to (or $\emptyset$ in case a recipe instance has not been selected for manufacturing) whereas the even elements inform about the recipe instance priorities. The proposed encoding is shown in Fig. 2. In this figure, $\pi_{j,k}$ and $p_{j,k}$ indicate the resource and priority assigned to recipe instance $\gamma_{j,k}$.

MOEA/D generates an initial population (a set of chromosomes) in a random way, in accordance with the resource affinities of the factory under consideration. The number of chromosomes in this population must be equal to the number of single objective optimisation subproblems decided earlier as each chromosome is assumed to be a solution of a certain subproblem. The Euclidean distances between the weight vectors corresponding to all pairs of chromosomes are computed and the closest neighbours are identified for each chromosome. Then, the algorithm is executed iteratively as long as a certain stopping criterion, for example reaching a predefined iteration number, is satisfied. In each iteration, a new generation is formed from the current one in the following manner. Firstly, the objective values (fitness) of each individual in the current population are computed using the algebraic model described in [3]. From the current population, two neighbouring chromosomes are selected randomly with the probability proportional to their fitness values and they form a pair of new chromosomes by exchanging their genes in a crossover process (a standard single-point crossover operator is applied). Then, the newly created individuals are mutated with a certain probability. Two mutation operators, shown in Fig. 3, can be used: the first one (Fig. 3 (left)) can change a recipe instance $\gamma_{j,k}$ allocated to resource $\pi_{j,k}$ into a recipe instance omitted in the manufacturing process or vice-versa (in the latter case, $\pi_{j,k}$ is chosen randomly from the resources compatible with $\gamma_{j,k}$). The second mutation operator (Fig. 3 (right)) is applicable to recipe instances allocated to any resource. It changes the manufacturing resource and the priority randomly ($\pi'_{j,k}$ must be compatible with $\gamma_{j,k}$). Finally, a custom elitism operator is applied. It selects the chromosomes whose surpluses for each produced commodity are the lowest and forms a new chromosome that contains the genes corresponding to these minimal surpluses. This individual is then added to the population by replacing a randomly chosen individual. This elitism operator is illustrated in Fig. 4. More details on the applied genetic algorithm can be found in [4].

5 Experimental results

The genetic approach briefly described in the previous section has been applied to the factory presented in Section 1. One of the major concerns related to the considered factory is the temporal unavailability of certain resources due to their malfunction or maintenance work. Hence, the first

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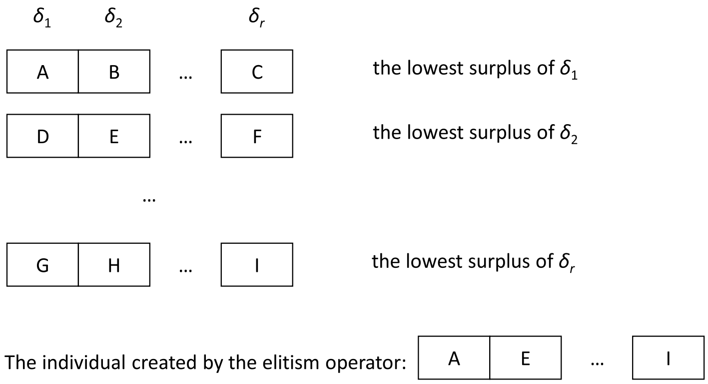

Figure 4: Customised elitism operator; A,D,G/B,E,H/C,F,I – a group of genes encoding recipes which manufacture commodity $\delta_1/\delta_2/\delta_r$.

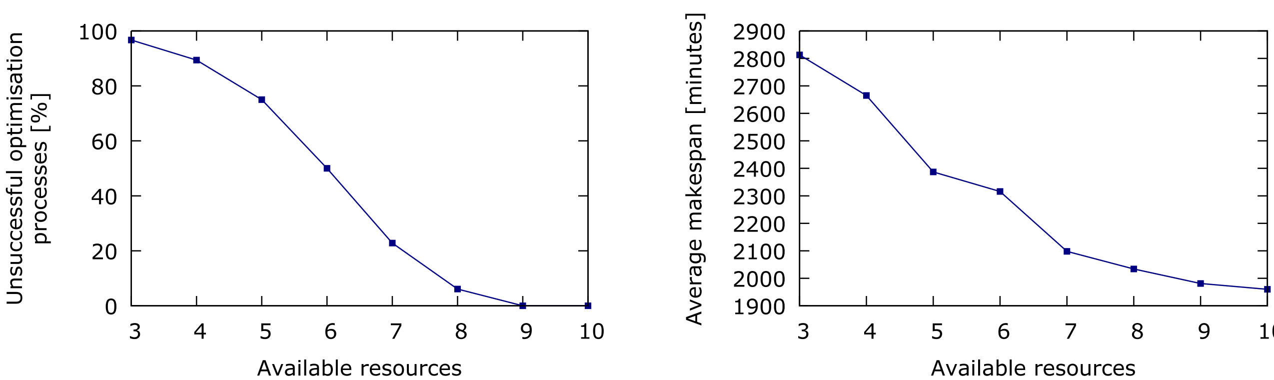

Figure 5: Influence of the resource unavailability on the number of successful optimisation processes (left) and makespan of manufacturing orders for different number of available resources (right).

experiment aimed at measuring the influence of such resource unavailability on the manufacturing process of the same commodity order. In total, 1800 optimisation processes have been executed, where the number of available resources varied randomly from 3 to 10. In Figure 5 (left), the percentage of successful optimisation processes is presented depending on the number of unavailable resources. The optimisation process fails when there is not a single resource available that satisfies the affinities of at least a single manufacturing processes. From the figure, it follows that in the cases of 9 or 10 available resources, all optimisation processes have been successful, which is understandable as each recipe can be executed on at least two resources. Consequently, even if one resource is unavailable, all recipes can be still processed. The situation changes when at least two resources are unavailable. For example, 6.1 % and 22.8 % of optimisation processes have been unschedulable with two and three unavailable resources (out of 10), respectively. For the extreme case of 3 available resources, not a single optimisation process has been successful.

Figure 5 (right) presents the average makespans of manufacturing orders of various capacity. As it is visible in the figure, when only 3 resources are available, the makespan is 1.45 times higher than when all (10) resources are available. Even unavailability of a single resource is penalised by 21 % in terms of the makespan. The makespan grows significantly when 4 or more resources are unavailable.

Next, the same genetic algorithm has been evaluated using real historic production data provided by a project business partner. Both the order volume and the project plan and schedule defined by a human expert operator have been extracted for a randomly selected day from the factory history as well as the actual recipe execution time. As a result, the usage time of the mixers needed to produce the ordered amount of commodities has been decreased by about 13 %, as shown in Fig. 6 (left). In Fig. 6 (right) it is clearly visible that before the optimisation a number of production lines were used more often than the remaining ones, whereas after optimisation the production line usage has been better balanced. This observation can be

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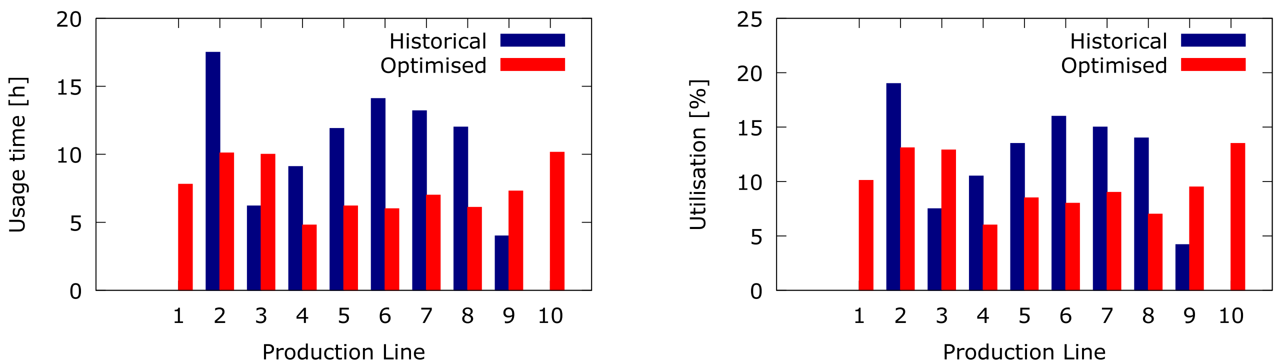

Figure 6: Comparison of usage time (left) and utilisation (right) per production line.

backed with the comparison of standard deviations of resource working time for historical and optimised schedule, which are equal to 6.75h and 2.62h, respectively.

6 Conclusion

In this paper, a real-world factory planning and scheduling problem has been described whose goal is not only to minimise the manufacturing makespan but also to minimise the production surplus via selecting recipes multisubset to be executed. This problem has been solved using a modified multi-objective genetic algorithm based on MOEA/D. The experiments have demonstrated the applicability of the proposed solution. In particular, the makespan of the obtained schedule is more than 10 % shorter than the real historic schedules generated by human experts and the standard deviation for production lines' utilisation has decreased by more than 60 %. The proposed approach applies to other plants that manufacture goods using alternative recipes while optimising one or more objectives.

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