Hybrid optimisation approach for sequencing and assignment decision-making in reconfigurable assembly lines

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Abstract: Technological advances, promoted by the Industry 4.0 paradigm, attempt to support the reconfigurability of manufacturing systems and to contribute to adaptive operational conditions. These systems must be responsive to significant changes in demand volume and product mix. In this paper, a hybrid optimisation approach is suggested to solve sequencing and assignment problems of reconfigurable assembly lines, where mobile robots collaborate with human operators. The objectives are: i) to define a schedule of jobs, ii) to assign tasks to the mobile robots, and iii) to decide the allocation of robots to workstations, in order to minimise the number of robots required. Preliminary results show that the proposed methodology can make an efficient robot allocation under high demand variety. In addition to that, the hybrid optimisation approach can be adapted to other configurations of assembly systems, which demonstrates its applicability to solve problems in other contexts.

Keywords: Reconfigurable assembly systems, Scheduling problem, Meta-heuristics, Hybrid optimisation.

1. INTRODUCTION

Manufacturing systems face a volatile demand with varying customer needs in terms of volume and product mix (Beauville dit Eynaud et al., 2019). These systems must be increasingly reconfigurable to react to these variations in a rapid and cost-effective manner (Koren et al., 2016). In this context, reconfigurable manufacturing systems (RMS) have been widely acknowledged as suitable for handling situations where responsiveness and productivity are of vital importance. Indeed, RMS provide a way to achieve a rapid and adaptive response to changes in volume and product mix (Leitao et al., 2012).

Here, planning and scheduling aim is to determine when and how to set a new configuration of the assembly line. The problem consists in deciding: i) which resources should be used to manufacture a single unit of product, and ii) the sequence the jobs should follow (Bensmaine et al., 2014; Nehzati et al., 2012). In short, solving this problem involves determining the optimal resources allocation and the job sequence. Although RMS is an active research field, and planning and scheduling have been widely investigated, these problems need to be studied under the Industry 4.0 paradigm. More specifically, attention should be given to the planning and scheduling of manufacturing systems, considering the introduction of novel technologies, such as mobile collaborative robots. First, by developing new modelling approaches for better understanding how new robotic technologies can be applied to design and run reconfigurable assembly systems (RAS). Second, addressing the modelling complexity of scheduling problems and the associated computational burden, through the development of alternative solution approaches, such as hybrid optimisation (Li and Xie, 2006).

The objective of this paper is to present a hybrid optimisation approach, that combines a constructive heuristic and a meta-heuristic, to solve sequencing and tasks assignment in reconfigurable assembly lines (RAL), where tasks can be divided between humans and collaborative robots that share the same workstation. The remainder of this paper is organised as follows. Section 2 discusses some existing works on planning and scheduling problems in RMS. Section 3 describes with more detail the problem addressed. Section 4 presents the proposed solution approach. The results are presented and discussed in Section 5. Section 6 presents some final remarks and future research work.

2. RELATED WORKS

Reconfigurability is an important ability that determines the ease and cost of reconfiguration. To enable reconfigurability, manufacturing companies must implement some core characteristics, such as modularity, integrability, diagnosability, adaptability and customisation. They facilitate the design of manufacturing systems to be reconfigurable, using hardware and software modules that can be integrated quickly and reliably (Koren et al., 1999). They also allow achieving the system's functionality and scalability required for the production of a product family to meet market demands (Maganha et al., 2018). Without them, the reconfiguration process will be lengthy or even impracticable (Koren et al., 1999). The core characteristics of reconfigurability are outlined in Table 1.

Table 1. Core characteristics of reconfigurability

Characteristic	Description
Modularity	Modular major components that can be reused and exchanged
Integrability	Ready integration of components and future integration of new technologies
Diagnosability	Detect and diagnose causes of unacceptable quality of products and reliability problems
Adaptability	Adapt system's capacity and functionality by means of an adjustable structure to changed or new situations
Customisation	Manufacturing systems are designed to produce a particular family of products

In a nutshell, *modularity* provides more adjustable production resources, capable of responding to unpredictable market demand. *Integrability*, on the other hand, allows the rapid integration of these available resources (Koren and Shpitalni, 2010). *Diagnosability* enables the fast detection of the quality problems after reconfiguration and contribute to reduce reconfiguration ramp-up time (Koren, 2013). Implementing *adaptability* is essential to cope with the scheduling function in RMS, since it allows adjustments in the capacity and functionality of the manufacturing system, by means of an adjustable structure (Maganha et al., 2018). In other words, it allows the modification of production capacity by adding/removing resources or changing system components (Koren et al., 1999). The same authors referred that diagnosability and adaptability complement each other, because scaling-up of an existing system to cope with changing demand requires a subsequent ramp-up period that can be reduced dramatically by implementing diagnosability. Finally, *customisation* aims at reducing the reconfiguration cost (Koren, 2013). These works suggest that there is the opportunity to apply optimisation approaches so as to improve the reconfigurability of assembly lines, by linking the core characteristics of reconfigurability with optimised planning and/or scheduling decision-making.

Recently, Bortolini et al. (2018) presented a structured and updated literature review on RMS, highlighting some works that have proposed solution approaches to solve scheduling problems in this context. Li and Xie (2006) applied genetic algorithm (GA) embedded with extended time-placed Petri nets (ETPN) for RMS scheduling, aiming to optimise reconfiguration costs and balanced production. Galan (2008) proposed a meta-heuristic approach to group products into families and then schedule these families, minimising the total cost. Prasoon et al. (2011) used a two-step optimisation approach to determine a reconfigurable set-up plan. The aim was to minimise costs and time of production, and achieve customers' specifications as closely as possible. Valente and Carpanzano (2011) proposed a dynamic algorithm to schedule automation tasks over time in RMS. The objective was to determine the sequence of automation tasks to be executed, in order to optimise the resource utilisation, considering deadline constraints. Chaube et al. (2012) proposed an adapted non-dominated sorting genetic algorithm II (NSGA-II) to generate a dynamic process plan for RMS. The authors considered a multi objective scenario, aiming at reducing manufacturing costs and time. Nehzati et al. (2012) used a fuzzy-based scheduling model to deal with the job assignment problem in RMS. In the model, the fuzzy logic system integrates dispatching rules and scheduling expertise to guide a dynamic selection of dispatching rules in job shops, minimising the total weighted. Azab and Naderi (2015) considered the problem of scheduling jobs in RMS. The authors applied a mixed integer linear programming (MILP) model, in order to determine the configuration and job sequence to minimise *makespan*. Hybrid optimisation approaches have been also used to solve this problem (Azab and Naderi, 2015; Li and Xie, 2006; Prasad and Jayswal, 2018).

Increased attention has been given to planning and scheduling problems in RAS. For instance, Meng et al. (2006) proposed a scheduling approach to realise the scalability and robustness of RAS. Gyulai et al. (2014) combined discrete-event simulation and machine learning techniques to handle the complex aspects of the planning problem of RAS. The goal was minimising the cost of production. Kumar et al. (2019) applied meta-heuristic optimisation techniques to address sequencing problems in RAS. Three objectives were considered: i) optimise the reconfiguration time and costs, ii) fulfil products due dates, and iii) fulfil the workload balance amongst the workstations.

However, despite the relevant contributions in this field, there is a dearth of literature considering manufacturing environments where the resources are assumed to be mobile and where robots collaborate with human operators. Research work in this field have been pursued by several authors (Giordani et al., 2009; Mosallaeipour et al., 2018; Nejad et al., 2018; Vieira et al., 2018; Yan et al., 2018). Our foremost contribution relies in a general hybrid optimisation approach to solve sequencing and task assignment in RAL, where human and mobile robots collaborate to manufacture products.

3. PROBLEM DESCRIPTION

The problem presented has been motivated by a manufacturing company that manufactures two different types of products (A and B). The products are assembled in a RAL composed of 10 workstations and mobile robots that can move among the workstations whenever necessary. The workstations follow a U-shaped layout, The assembly of the products require the execution of a set of tasks, each one with a given processing time and precedence constraints. Both product types have tasks that are performed by humans and mobile robots. Tasks performed by humans are common to both products, while tasks performed by robots are specific to each product type. There is one human operator in each workstation to perform the common tasks. All specific tasks are performed by multitasking mobile robots that can coexist with humans in a workstation. The displacement time of robots among workstations is considered negligible. More than one robot is allowed at a workstation, at a time. Nevertheless, a robot cannot perform more than one task at a time and pre-emption is not allowed.

The production plan of the assembly line is defined in a weekly basis, containing the list of products to be manufactured. Thus, the weekly demand plan of products required to feed the assembly line represents a list of jobs to be produced, including the quantity to be produced in the week, the list of tasks to be performed in each workstation, the set of precedence constraints of tasks of each product, and the corresponding processing times of each task. The workstation line cycle time is determined by the tasks performed by the human operators. This means that, in each workstation, the time taken by the robot(s) to perform their operations must be equal or lower than the time required to the human to perform its operations.

The problem can be stated as follows − a set of jobs, *i.e.*, a set of products, has to be assembled in the line. Each job is composed by a set of specific tasks to be performed by mobile robots in each workstation. The problem consists in determining the sequence of jobs and assigning tasks to robots, minimising the number of robots required to achieve the cycle time desired. To address the problem, the main process data considered, for the workstation 1 (WS1) is shown in Table 2.

Table 2. Data of tasks to be performed in WS1

Product	WS1			
	Task_ID	Task type	Processing time (s)	Precedent task
A	task_0	transport	4.8	
	task_1	specific	9.0	task_0
	task_2	specific	3.0	task_1
	task_3	specific	6.0	task_1
	task_5	specific	1.8	task_3
	task_100	common	30.0	
B	task_0	transport	4.8	
	task_4	specific	4.8	task_0
	task_21	specific	7.2	task_0
	task_22	specific	7.2	task_0
	task_23	specific	7.2	task_21, task_22
	task_24	specific	7.2	task_21, task_22
	task_25	specific	9.0	task_23, task_24
	task_100	common	30.0	

Task_0 is the transportation time between the initial buffer and WS1 or between two consecutive workstations. This time is constant for all workstations. This means that, after leaving a given workstation the product will take 4.8s to reach the next one. Then, the human operator can begin the execution of the set of common tasks, which were allocated to it (task_100). The set of tasks allocated to humans on each workstation have a common total processing time (30s), corresponding to the assembly line cycle time desired. While the human operator is performing the common tasks, one or more collaborative robots are called to the workstation to perform, in parallel, the product specific tasks.

4. PROPOSED APPROACH

The proposed hybrid optimisation approach uses a meta-heuristic and a list algorithm. The principle of the method is given in Fig. 1. The encoding used by the meta-heuristic is a list Y of jobs. The list algorithm considers the jobs in the list order and assign their tasks to the required mobile robot, respecting the problem constraints. This builds the solution X. The objective function H evaluates the solution X. According to this evaluation, the solution is chosen or not by the meta-heuristic. At the end of the running, the solution given by the hybridisation is the best list (sequence) of jobs: the one that optimises the objective function by applying the list algorithm (Klement et al., 2017b).

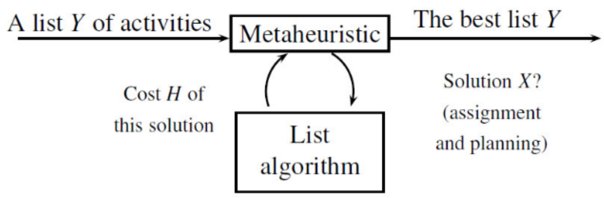

Fig. 1. Hybridisation of a meta-heuristic and a list algorithm

Several planning and scheduling problems have already been solved with this hybrid optimisation approach (Klement et al., 2017a; Mazar et al., 2018; Silva et al., 2018). This demonstrates that this approach can be adapted to several problems variants (Silva and Klement, 2017).

4.1 Meta-heuristic

The stochastic descent was the based meta-heuristics chosen, due to the easiness of application, thus, speeding up the development process (Silva and Klement, 2017). The objective was to obtain results rapidly, to evaluate the ability of the proposed approach to solve the tasks assignment and sequencing problems of the RAL studied. In detail, the meta-heuristic performs in the set of all lists Y. An initial solution is randomly computed: a list of jobs randomly sorted between one and the number of jobs. A neighbourhood is used to visit the set of solutions, allowing to go from one solution to another. The neighbourhood V is a permutation of two jobs in list Y: the job at position i permutes with the job at position j, with i and j being two different random numbers.

4.2 List algorithm

This hybridisation can be used to solve many problems, provided that the list algorithm and the objective function are adapted according to the problem considered, by integrating the different constraints that rule the problem and the objective to be improved. The list algorithm is used to build the solution X from the list Y: it assigns the tasks to the mobile robots over the horizon planning, according to the problem constraints. List scheduling algorithms are one-pass heuristics that are widely used to make schedules. It is important to work with a list algorithm, because the meta-heuristic browses the set of lists Y. So the used algorithm needs to consider the order of the list to assign the tasks to resources over the planning horizon (Klement et al., 2017b). The list algorithm developed is outlined in Algorithm 1.

Algorithm 1 List algorithm

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Input: list of products, list of tasks, processing times of each task
Output: sequence of jobs, assignment of tasks to robots, allocation of
    robots to workstations
for all products in the list do
    for all workstations do
        for the list of tasks do
            while there are tasks to be performed do
                if the task requires a robot then
                    if there are no robot in the workstation then
                        for all robots do
                            if the robot is available then
                                Call the robot to the workstation
                                Assign the task to the robot
                                Update robot's release time
                            else
                                Update the list of tasks to be performed
                    else
                        if the robot is available then
                            Assign the task to the robot
                            Update robot's release time
                        else
                            for all robots do
                                if the robot is available then
                                    Call the robot to the workstation
                                    Assign the task to the robot
                                    Update robot's release time
                                else
                                    Update the list of tasks to be per-
    formed
```

4.3 Objective function

Solutions are compared according to an objective function that characterises the quality of the solution. The aim is to find the solution X that minimises the number of robots required to achieve the cycle time desired. The set of all lists Y of jobs is browsed thanks to the meta-heuristic, using the neighbourhood V. Lists are compared by the list algorithm and the objective function. According to an acceptance criterion, some lists are selected. At the end, the meta-heuristic gives the best list Y found.

5. PRELIMINARY RESULTS

In Table 3, the demand generated for each product for a sequence of 4 weeks is presented.

Table 3. Demand of products (in units)

Product	Week 1	Week 2	Week 3	Week 4
A	256	178	190	304
B	256	118	284	304
Total	512	296	474	608

The *makespan* and the number of robots obtained for each week are presented in Table 4.

Given the dimension of the problem and the number of specific tasks for each product, only a sample of the assignment of tasks to the robots is presented in Table 5.

Table 6 presents a small part (15 consecutive jobs) of the sequence obtained in each week. It can be seen that the optimal job sequence seems to be more impacted by job product mix than by production volume. In fact, the sequence obtained for week 1 and 4 with same product mix but different production volumes are equal, but different from sequences for week 2 and 3 which have different product mixes.

The RAL studied was designed to assemble a single product family, composed by products A and B. In Table 3, the product's demand fluctuates during the four weeks: from week 1 to week 2, it decreases 42%; from week 2 to week 3, it increases 28%; and from week 3 to week 4, it increases 22%. The percentage of the product mix also vary: in weeks 1 and 4, there is a demand of 50% of product A and 50% of product B; in week 2, 60% of A and 40% of B; and in week 3, 40% of A and 60% of B. This RAL can cope with all these frequent changes in market demand and product mix. This means that the RAL can adjust its capacity and functionality to abrupt changes on market demand. Indeed, the multitasking mobile robots characterise highly adjustable resources, which can change their functionality whenever necessary, in order to cope with changes in demand or product mix. Furthermore, to move from one workstation to another, these robots must be integrated. These are evidences that this RAL has four of the five core characteristics of reconfigurability implemented: customisation, adaptability, modularity and integrability.

In weeks 1, 3 and 4, the highest volumes are required, but the lowest number of robots is needed. In these weeks, the product mix varies between 50% of A and 50% of B, and 40% of A and 60% of B. In week 2, the lowest volume is required, but the highest number of robots is needed. Thus, when the mix of product includes more than 50% of products A, more robots are required. However, when the product mix includes more than 50% of products B, the number of robots needed does not increase. This may be justified by the number of specific tasks of each type of product; product A has 19 specific tasks and product

Table 4. Results obtained using the hybrid approach

Item	Week 1	Week 2	Week 3	Week 4
Makespan	15630	9150	14490	18510
Number of robots	13	15	13	13

Table 5. Results: assignment of tasks to robots

Robot	Product	WS	Task	Starting time	Release time
1	1	1	1	4.8	13.8
1	1	1	2	13.8	16.8
2	1	1	3	13.8	19.8
...	...	...	...	...	...
2	511	10	34	15583.8	15598.8

Table 6. Part of the sequences obtained for each week

Week	Sequence
1	[A,B,A,B,A,B,A,B,A,B,A,B,A,B,A,...]
2	[B,A,B,B,A,B,B,B,A,A,A,B,A,A,A,...]
3	[B,A,B,A,B,A,B,A,B,A,B,A,B,A,B,...]
4	[A,B,A,B,A,B,A,B,A,B,A,B,A,B,A,...]

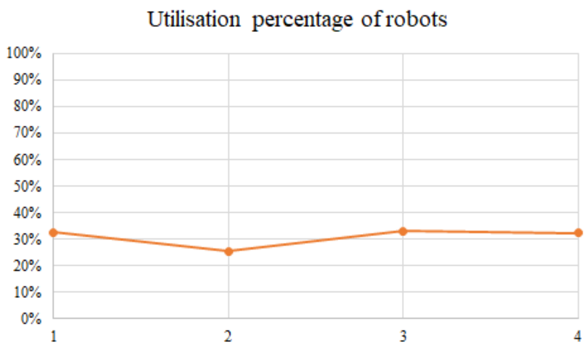

Fig. 2. Utilisation percentage of robots in each week

B has 15. Thereby, while product demand impacts on the *makespan* (the highest the volume, the highest the *makespan*), product mix impacts on the number of robots needed to perform the specific tasks

The utilisation percentage of robots are presented in Fig. 2.

As can be seen, the utilisation percentage of robots is around 40%. Therefore, in this RAL, managers should analyse the trade-off between achieving the minimum *makespan* and investing in mobile robots that might have low utilisation percentages.

6. CONCLUSION

Results show that the RAL proposed can cope with high demand variety in terms of mix and volume. In this case, the demand variety can be accommodated by changing the number of collaborative robots in use and the tasks allocated to each one.

To solve the sequencing and assignment problems in the RAL, this paper proposes a hybrid optimisation approach, that combines a list algorithm with a meta-heuristic. This approach allowed to obtain a good sequence of products, the number of robots needed and the assignment of tasks to the robots that minimise the number of robots required. The proposed approach was tested using a large-scale instance, showing its ability to solve real-world problems. The metaheuristic used was the stochastic descent. The encoding of more efficient meta-heuristics, e.g. simulated annealing, is envisaged as a development. Previous research work in the field of RMS has shown that simulated annealing may provide interesting solutions in reduced computational time (Rabbani et al., 2014).

Future research should consider further constraints, such as considering displacement time for robots in the assembly line, and setup times when the robot change from one task to another, to obtain a more realistic approach of the problem. Moreover, the integration of robots assistance in manufacturing is a relevant research concern (Giordani et al., 2009). Evaluating these and other evolvable aspects of the Industry 4.0 paradigm will allow the design and operation of quite efficient RAL.

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