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Simulation-based optimization approach with scenario-based product sequence in a reconfigurable manufacturing system (RMS): A case study

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Abstract: In this study, we consider a production planning and resource allocation problem of a Reconfigurable Manufacturing System (RMS). Four general scenarios are considered for the product arrival sequence. The objective function aims to minimize total completion time of jobs. For a given set of input parameters defined by the market, we want to find the best configuration for the production line with respect to the number of resources and their allocation on workstations. In order to solve the problem, a hybridization approach based on simulation and optimization (Sim-Opt) is proposed. In the simulation phase, a Discrete Event Simulation (DES) model is developed. On the other hand, a simulated annealing (SA) algorithm is developed in Python to optimize the solution. In this approach, the results of the optimization feed the simulation model. On the other side, performance of these solutions are copied from simulation model to the optimization model. The best solution with the best performance can be achieved by this manually cyclic approach. The proposed approach is applied on a real case study from the automotive industry. Copyright © 2019 IFAC

Keywords: Simulation-Based Optimization, Reconfigurable Manufacturing System (RMS), Reconfigurability, Simulated Annealing (SA).

1. INTRODUCTION

Nowadays, rapid and global data transformation, open market and changeable demand compel manufacturing systems structure to change. According to the new technologies, new product variety and high demand fluctuation for different products, production systems should be more flexible. They must be able to react and response quickly in face of these changes. The traditional manufacturing systems were not able to handle these challenges. The Dedicated Manufacturing System (DMS) has a high throughput but very low flexibility to produce different product part families. The Flexible Manufacturing System (FMS) consists of full automated components with high flexibility to response a stable demand of products. The Reconfigurable Manufacturing System (RMS) can overcome the limitations of these systems. RMS is part of Industry 4.0, aiming to cover high flexibility of FMS and high throughput of DMS. It is also able to adjust rapidly in context of functionality and productivity by rearranging existing components. Because RMS is needed in the new generation of manufacturing systems, it is an important subject. The RMS is capable to cover a variable demand. Hence, this system is a dynamic system. According to the variable demand in real world systems, reconfigurability of machines and system structure is an effective point of RMS. Moreover, with respect to the extension of market competition and decreasing production costs, using RMS leads system to progress in this situation.

This study focuses on proposing a manufacturing system enabling assembly of two different types of products: diesel engines (abbreviated DVR in the following paragraphs) and gasoline engines (EB). A production planning problem of a RMS is investigated. To calculate total completion time of the system, four general scenarios for the product sequence are considered. Task assignment to the workstations and their sequence in each station are already known. Lower and upper bound for the number of machines in each station are defined.

2. LITERATURE REVIEW

According to the evolution of manufacturing systems, each of them have their own special advantages and disadvantages. In the dedicated manufacturing system (DMS), automation and structure are fixed. A possibility to produce in a high throughput is the main advantage of the DMS (Koren and Shpitalni, 2010). Moreover, the fixed structure of DMS is unchangeable either to manufacture various products or to increase throughput of the system (Koren et al., 2017). The Flexible manufacturing system (FMS) had been introduced after DMS (Katz, 2007). These systems can adapt to many manufacturing requirement easily and quickly (Abele et al., 2006). FMS has been extended to make possibility structure to adjust and scale the capacity quickly within producing part families (ElMaraghy, 2007). The RMS has been introduced by Koren et al. (1999). The efficiency is high in the context of responsiveness to sudden changes of the market (Battaïa et al, 2017). The RMS is an adjustable system regarding capacity

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and functionality. In fact, the RMS covers advantages of both previous manufacturing systems (Bi et al., 2008) and also overcome some disadvantages of the FMS such as high cost, obsolescence, unfavourable tools, and unreliability (Mehrabi et al., 2000). One of the main differences between FMS and RMS is the customized flexibility of RMS and the general flexibility of FMS. Customized flexibility means that the system can be changed whenever it is needed (Wiendahl et al., 2007). A whole comparison of these three manufacturing systems have been proposed by (Zhang et al., 2006), (Koren and Shpitalni, 2010) and (Koren et al., 2017).

Researchers worked on process planning in RMS; Chaube et al. (2012) proposed an NSGA-2 algorithm to solve an RMS process planning problem. Firstly, they assigned tasks to a set of reconfigurable machines, and then optimized the completion time and cost by scheduling these tasks. In this study, machines are not the same, and they have their own set of reconfigurations. In an other study, Prasoon et al. (2011) worked on optimization of reconfigurable set-up plans in a dynamic production system by studying an algorithm portfolio approach.

Basically, simulation modelling is an efficient approach to handle the complex systems under uncertainty (Borshchev and Filippov, 2004). Simulation should be used as an approach to evaluate complex systems (Juan et al., 2015). Discrete Event Simulation is the procedure of modelling by considering different changes over time (Chica et al., 2017). On the other hand, optimization gives the possibility to find the best parameter combination in order to run the system efficiently. The right optimization method should be selected depending on the faced problem. Exact methods provide optimal solution for small size problems and metaheuristics can solve NP-hard problems (nondeterministic polynomial time problems), providing near optimal solution. For instance, Dou et al., (2009) proposed a genetic algorithm (GA) to find some of the best configurations among all the optimal configurations that had been obtained by some feasible generated sequences. A systematic approach to generate different feasible configurations for the single-product RMS was developed. Combination of simulation models and these optimization methods enhances the solution. Hybridization of simulation and metaheuristics provides interesting results because of its ability to provide high quality solutions for NP-hard real problems in reasonable calculation time (Juan et al., 2015). Gansterer et al. (2014) proposed a simulation-based optimization method to assess some parameters in production planning. Fu (2002) proposed a classification of hybridization approaches based on simulation and optimization, namely, simulation-based optimization and optimization-based simulation. Optimization and simulation phases connect with each other by different interfaces. These interfaces may be user-defined (Dehghanimohammadabadi et al., 2017) (Attar et al., 2017) or general tools like Excel software (Dehghanimohammadabadi et al., 2017). Simul8 is a good software to implement a Discrete Event Simulation (DES) model (Carteni and De Luca, 2012). Imran et al. (2017) linked DES and different metaheuristics.

3. PROPOSED APPROACH

3.1 Problem Description

Among the different paradigms to build a reconfigurable production system, the integration of mobile robots on the production system has been selected in order to enable easy reconfiguration of the production line. This choice is made based on the assumption that there exists a safety system enabling the integration of a collaborative robot on a movable platform. The reconfiguration of the production system consists in the reallocation of the movable robots on workstations. This occurs when the system is subject to fluctuations of the economic context, leading to changes of the production demand in volume or product variety. This paper focuses on product variety.

In this study, we consider two objective functions aimed to minimize total completion time. The system contains m workstations with specific assigned tasks to produce p product types. The problem is about allocation of n identical mobile robots to the workstations. s = 1,2,…,m , r = 1,2,…,n and k = 1,2,…,p respectively are sets of stations, robots and product types. As parameters of the model, P_k and c_{rs} are respectively the price of the product k and cost of per percent utilization of robot r on station s. These parameters are fixed. On the other hand, two other parameters are obtained by simulation: the number of final products k (N_k) and the utilization percentage of assigned robots to station s (u_s). In the proposed model, two binary decision variables x_{rs} and y_{rs} are 1 if robot r is assigned to station s respectively for producing DVR and EB, and one continuous variable C_T representing total completion time. Task sequence of each product and processing time are already known. Lower and upper bound are considered for the number of robots in the stations. To calculate completion time, different scenarios are defined for product arrival. The objective function maximizing profit is calculated by (1) and the objective function minimizing completion time is presented by (2).

$$Max\, z_1 = \sum_{k=1}^{p} N_k\, P_k - \sum_{s=1}^{m} u_s \sum_{r=1}^{n} (x_{rs} + y_{rs})\, c_{rs} \quad (1)$$
$$Min\, z_2 = C_T \quad (2)$$

3.2 Methodology

To model the proposed problem, an efficient DES model was developed using Simul8 tool. The simulation model is running with respect to the demand of specific period, in our study during one week. Tasks sequence, tasks duration, product mix ratio, and generated robot allocation are input parameters of the simulation model. Utilization of robots (in percentage of the total simulated time) and the number of final products are output parameters of this model which are considered as input parameters of the optimization phase (Fig. 1). The optimization module generates a new resource allocation, which is used as input for the next simulation run, and so on. Input parameters of the simulation model, as Excel file, are imported in Simul8. The simulation model is developed to provide insights into the workflow process, calculate the utilization percentage of resources, and obtain the number of final products.

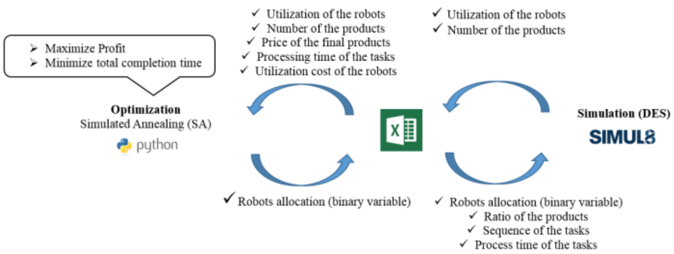

Fig. 1. Schema of the proposed hybridization approach.

A Simulated Annealing (SA) algorithm was developed in Python for the optimization phase, presented Fig. 2.

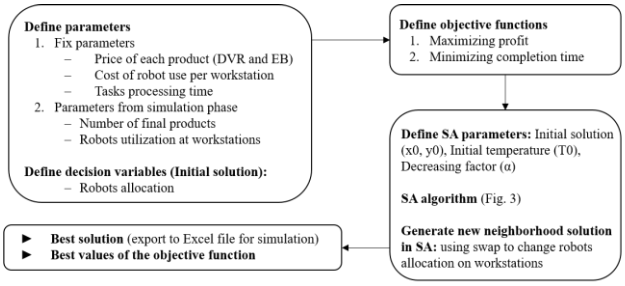

Fig. 2. Schema of the optimization phase

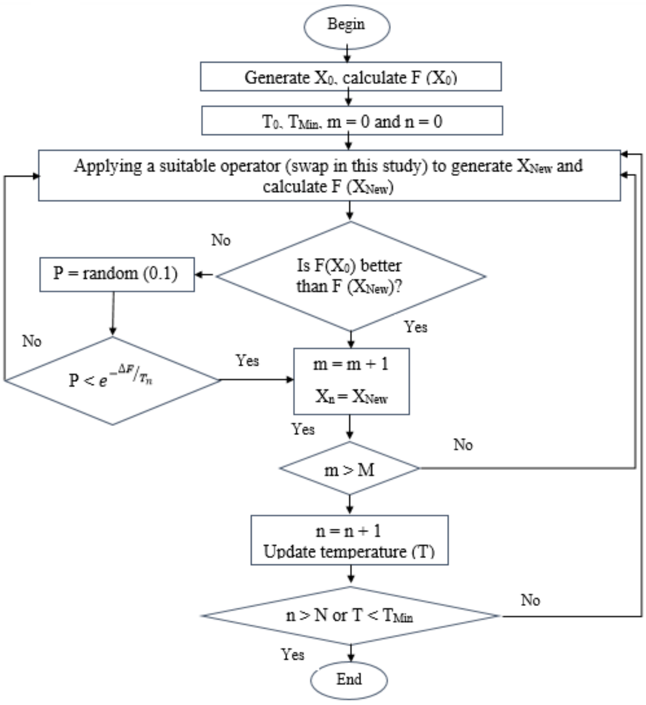

Fig. 3. Flow chart of SA

In the proposed SA, detailed in Fig. 3, a random generated solution is used as initial solution with an initial temperature, and neighbourhood solutions are generated by changing robot allocation on different stations according to a swap structure. If the newly generated solution improves the objective function, this last one is saved. However, keeping a worse solution is authorized according to a predefined probability, which decreases at each iteration of the algorithm. The temperature of the SA is updated, which reduces the acceptation of a worse solution for the next step, and the cycle is repeated. After a predefined number of iterations, the algorithm stops.

SA is applied to solve the two objective functions, minimizing completion time and maximizing the profit value. Torabi and Hassini (2008) introduced the so-called TH method, based on a fuzzy approach, used to solve the bi-objective model.

4. APPLICATION TO A CASE STUDY

4.1 Case Study: an Automotive Assembly System

In this study, we consider the engine assembly system of an automotive company as a case study. The factory aims to improve its current system and make a reconfigurable manufacturing system. In this company, two types of engines, diesel and gasoline, are assembled. These engines are respectively called DVR and EB. Four assembly station are investigated in this study. The assigned tasks to workstations and their sequence is shown by Fig. 4.

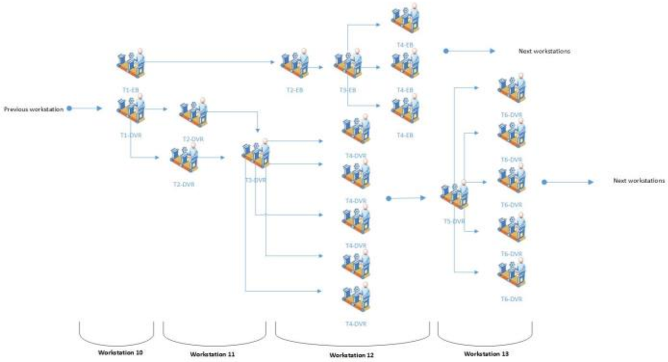

Fig. 4. Precedence of the assigned tasks to the workstations.

Reconfigurability is reached by having mobile collaborative robots on AGVs. These robots are the resources we target to assign to workstations, depending on the current product mix and product sequence. The considered problem is production planning and resource allocation problem for the reconfigurable system. Actually, we want to evaluate the effect of reconfigurability on the current system. Thereby, two models with two different objective functions are considered in optimization phase. The objective functions are maximizing the profit of company and minimizing the total completion time. The assumptions considered in this study are:

- Each robot should be assigned to only one workstation at the same time.
- Conveyor starts moving when the last product is released in the stations.
- The total completion time is calculated with respect to the four proposed scenarios and the number of assigned robots to the workstations.
- There is an upper-bound for the number of assigned robots to the workstations. The maximum number of robots which can be assigned to each workstation is equal to the maximum number of parallel tasks in the workstation.
- At maximum one robot can be assigned to workstation 10.
- At maximum two robots can be assigned to workstation 11.
- The maximum number of robots which can be used in workstations 12 and 13 are 5.

- At least one robot should be assigned to each workstation.
- The maximum number of existing product in each workstation at each time is one product.
- The assigned tasks to the workstations are already known.
- DVRs and EBs have some common tasks and some specific tasks.
- Tasks sequence for each type of product are already known.

Different scenarios are considered for the product sequence in assembly line. For example, in a scenario DVRs are assembled and then EBs can be assembled (Fig. 5), and this scenario can be considered vice versa as second scenario (Fig. 6). In other scenarios, products might be assembled alternately, in which they can be started with a DVR (Fig. 7) or an EB (Fig. 8). In these scenarios the ratio of the number of DVR engines and EB engines can be different. In these figures, 1 robot in workstation 10, 2 robots in workstation 11, 5 robots in workstation 12 and 13 are assumed. Considering the relative ratio between the products is the main point in these scenarios. For example, the number of DVRs may be greater than EBs or vice versa.

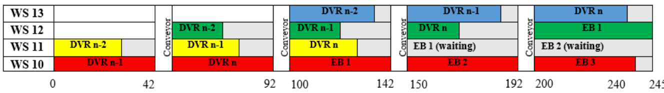

Fig. 5. Assembly line for assembling all DVRs before EBs.

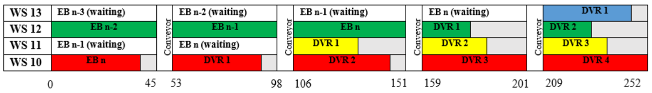

Fig. 6. Assembly line for assembling all EBs before DVRs.

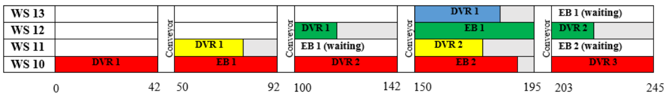

Fig. 7. Assembly line for assembling products alternately, starting with DVR.

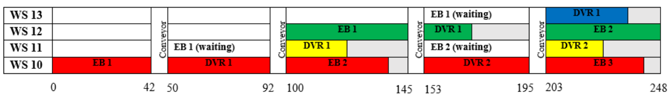

Fig. 8. Assembly line for assembling products alternately, starting with EB.

According to the number of assigned robots to the workstations, the defined scenarios and the processing time of tasks, total completion time of each station can be calculated. These values, presented in Table 1, are considered in 10^{-2} min.

Table 1. Completion time of each station with respect to the number of assigned robots (Unit: 10^{-2} min)

Nb of robots		WS 10	WS 11		WS 12				
		>=1	1	>=2	1	2	3	4	>=5
DVR	C_T	42	56	31	85	51	34	34	17
EB	C_T	42	0	0	79	62	45	45	45

Nb of robots		WS 13				
		1	2	3	4	>=5
DVR	C_T	110	70	60	50	40
EB	C_T	0	0	0	0	0

4.2 Results and Discussion

A SA algorithm is developed to solve separately each objective function. A feasible random initial solution is generated. After 2000 iterations of the SA algorithm, the best profit value is obtained. The solutions for robot allocation to the stations are shown for DVRs (Fig. 9) and EBs (Fig. 10).

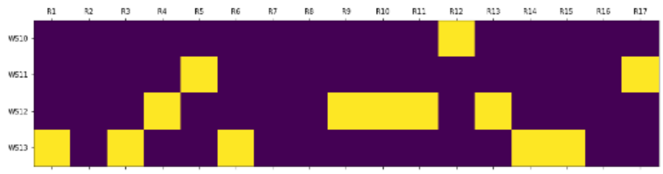

Fig. 9. Best robot allocation to the workstations maximizing profit value for assembling DVRs (X*).

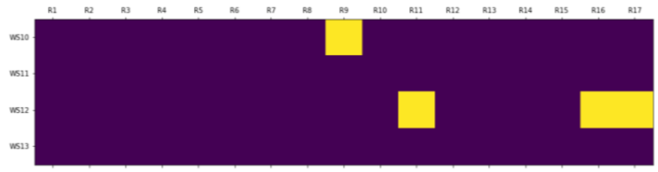

Fig. 10. Best robot allocation to the workstations maximizing profit value for assembling EBs (Y*).

After 2000 iterations, the minimal completion time is 2269 min with a 50-50 ratio of the two types of products (Fig. 11). Obtained solutions for robot allocation to the stations are shown for DVRs (Fig. 12) and EBs (Fig. 13). Scenario 2 is the best scenario for product sequence with respect to given number of products.

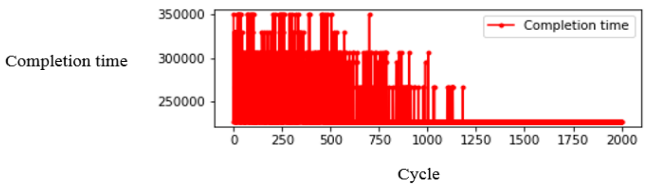

Fig. 11. Completion time values (10^{-2} min).

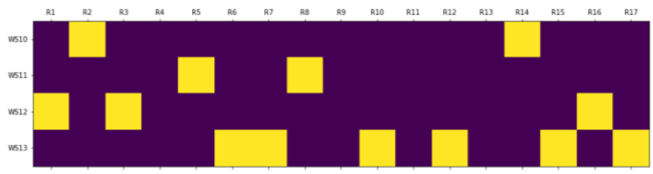

Fig. 12. Best robot allocation to the workstations minimizing completion time for assembling DVRs (X*).

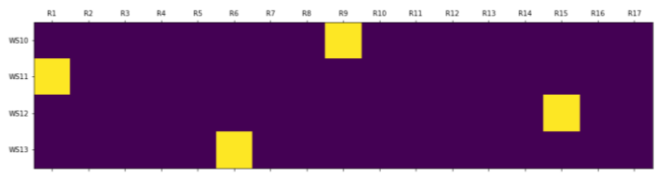

Fig. 13. Best robot allocation to the workstations minimizing completion time for assembling EBs (Y*).

To implement TH method for solving the bi-objective model, *Z*-positive ideal solution (Z^{PIS}) and *Z*-negative ideal solution (Z^{NIS}) for two objective functions are needed (Table 2).

Table 2. Z_{PIS} and Z_{NIS} for minimizing completion time

	Z^{PIS}	Z^{NIS}
Second model (minimize completion time function) (min)	2269	3501

Table 3. Values of the objective function with respect to different parameters of TH

ϑ	(φ_1, φ_2)	μ_1	μ_2	Z_2 (min)
0.2	(0.2, 0.8)	0.579	0.999	2269
0.2	(0.5, 0.5)	0.610	0.999	2269
0.2	(0.8, 0.2)	0.686	0.670	2668
0.5	(0.2, 0.8)	0.642	0.999	2269
0.5	(0.5, 0.5)	0.648	0.999	2269
0.5	(0.8, 0.2)	0.650	0.670	2668
0.8	(0.2, 0.8)	0.562	0.999	2269
0.8	(0.5, 0.5)	0.668	0.999	2269
0.8	(0.8, 0.2)	0.690	0.670	2668

According to Table 3, it can be concluded that if the importance of an objective function (φ_i) increases, this objective function will be improved and vice versa. It also should be said that the satisfaction degree of each objective function will increase by changing ϑ. Moreover, the Pareto frontier of the problem was provided.

The objective function values for different product ratios are listed in Table 4. These different values with respect to the different numbers of DVRs and EBs are shown Fig. 14.

Table 4. Completion time values for different number of products

Number of DVRs	Number of EBs	Completion time value (min)	Best scenario
0	5000	2251	1
1000	4000	2301	1
2000	3000	2351	1
2349	2438	2269	2
3000	2000	2061	3
4000	1000	1031	3
5000	0	182	3

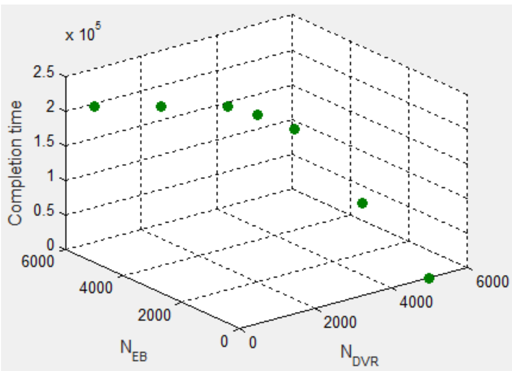

Fig. 14. Completion time values for different number of products.

The best scenario of product sequence with respect to the demand variety can be selected. Regarding results depicted in Table 4, it is preferable to use scenario 1 (assembling all DVRs before EBs) when the EB ratio is higher, and use scenario 3 (assemble products alternately) when the DVR ratio is higher.

5. CONCLUSION AND FUTURE STUDY

In this paper, a general concept of hybridization approach based on simulation and optimization is implemented. It is developed to solve production planning and resource allocation problem in a reconfigurable manufacturing system (RMS). Solutions obtained in the optimization phase are then evaluated using the developed simulation model. In this approach, some parameters are obtained from simulation and imported into the optimization to give an efficient resource allocation structure. A metaheuristic (SA) has been applied on the problem to determine the best configuration to achieve a minimal completion time with maximization of the profit function. Consequently, it can be concluded that the proposed approach provides a good performance for design and production planning problems of RMS. Moreover, regarding defined scenarios for product sequence, the best scenario can be chosen with respect to the demand variety of product families.

As a future study, other optimization algorithms could be tested to solve this problem. Furthermore, the methodology could be applied to an extended use case with a higher number of workstations and resources, meaning a higher degree of complexity. The hybridization between simulation and optimization has also to be continued, as the communication between the different modules is not fully automatized yet.

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