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A New Process Quality-based Multi-objective Multi-part Approach for the Integrated Process Planning and Scheduling (IPPS) Problem in Reconfigurable Manufacturing Environment

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Abstract: This paper addresses the so-called integrated process planning and scheduling (IPPS) problem in a reconfigurable manufacturing environment. Process planning and scheduling are two important and complex functions in manufacturing. To reduce the problem complexity, they are considered sequentially by traditional approaches. In this paper, we consider the simultaneous integration of both functions by developing a heuristic approach to solve the IPPS problem in a reconfigurable environment. Reconfigurable manufacturing systems (RMSs) comprise of a set of machines distinguished by multiple working configurations and tools. Each machine can perform a certain number of operations based on its configurations and their availability. The purpose of the proposed heuristic approach is to find the best assignment of operations to machines while considering process-quality. Finally, to demonstrate the approach applicability, an illustrative numerical example is presented and the results discussed.

Keywords: reconfigurable manufacturing system, process plan, scheduling, IPPS, quality, MOILP

1. INTRODUCTION

Nowadays, manufacturing environments are continuously evolving following the continuous development of technologies and knowledge. Different production paradigms allow a better coping with the current trends such as the increased level of customization, the high market demand fluctuation and the reduced product life cycle. In this context, several companies are using dedicated manufacturing system (DMS) and flexible manufacturing system (FMS) as two effective solutions.

DMS involves the production of one item at a time. It is cost effective in the case of mass production but lacks in the variety. FMS guarantees the production of multiple items but the initial investment increases with increasing cost inefficiencies and lower performance for the industrial organization. Moreover, the continuous demand for products incorporating new and complex functionalities rises the pressure on the manufacturing companies. An effective response to market changes requires new manufacturing approaches that not only combine the high throughput of DMS with the flexibility of FMS, but also that are able to react to changes quickly and efficiently.

In recent years, reconfigurable manufacturing system (RMS) arose as the natural evolution of the existing systems, in response to their deficiencies. According to ElMaraghy (2005), RMS consists of a complex system designed to match the key advantages of DMS and RMS, namely production capacity and flexibility.

The core issue of a RMS, as defined by Koren *et al.* (1999), lies in the ease and rapid adjusting of machines according to the production needs thanks to the replacement, addition or removal of functional modules. Each machine has a given number of configurations, depending on the module compatibilities and a set of available operations for each configuration. These features allow RMS to match the Industry 4.0 paradigm. The aim of the fourth industrial revolution is to develop an automation-driven environment in which machines and IT infrastructures are connected to collect Big Data to be analysed. On the other hand, further co-operation between men and machines aiming at high QoL (Quality of Life) values is needed, which implies the development of high-quality products and deep customization.

Behind the industrial revolution achievements, there are several challenges to be faced. The technological progress is probably the most obvious even if support functions, such as process planning, process and production control strategies and logistics emerge as enabling activities, *"which must not only be in place but also be adaptable and well-integrated for any successful and economical responsiveness to changes in manufacturing to materialize"* (ElMaraghy, 2007).

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This paper focuses on the development of a new process quality-based multi-objective multi-part approach for the integrated process planning and scheduling (IPPS) problem within reconfigurable environments. We propose a multi-objective integer linear program (MOILP) formulation including product quality considerations. To solve the model a heuristic approach is developed to design a sequential operation assignment criterion while considering alternative solutions and their resultant losses.

According to the introduced topic and goal, this paper is organized as follows: Section 2 reviews the existing literature on IPPS and RMS. Section 3 states the problem and its mathematical model. Section 4 overviews the proposed heuristic approach. Section 5 details an illustrative numerical example. Finally, Section 6 concludes this paper outlining future work directions.

2. LITERATURE REVIEW

According to Salvendy (2001), the process plan/process planning (PP) is "*the determination of components needed to produce a part, and the necessary operations to transform the raw materials into a finished product". Moreover, it is well known that process planning is different than scheduling. In fact, scheduling can be defined as the assignment of operations to each resource in order to accomplish the process plan*", where the sequences of operations are allocated according to given criteria, e.g. lower make-span, due-date, etc.

According to these definitions, process planning and scheduling are two separate activities. Scheduling assumes a fix process plan, but, in practise, scheduling conflicts force the change of the process plan following their source availability. Moreover, the scheduling problem itself is a well-known NP-hard optimization problem. Integrating it with the process planning makes the forthcoming IPPS problem complexity of several orders of magnitude larger.

Chen and Khoshnevis (1990) developed a heuristic algorithm based on opportunistic planning to integrate process planning and scheduling assuming a sequential assignment of jobs to machines. Sequential assignment approaches usually do not consider relationship dynamics between scheduled and not yet scheduled resources. For this reason, Kim *et al.* (2003) proposed a symbiotic evolutionary algorithm considering population interactions. An artificial intelligent search technique is used to consider simultaneously the two objective functions related to process planning and scheduling, minimizing the makespan and the mean flow time for all jobs. With the introduction of RMSs, ElMaraghy (2007) improved the previous definition of PP proposing a new classification based on granularity. Multi-domain process planning deals with the choice of the most suitable manufacturing technologies to use; macro process planning deals with selecting the best sequence of processing steps and setups as well as of the machines to use and micro process planning details the execution instructions and numerical control program steps. Consequently, the IPPS problem complexity has increased further due to the high flexibility of technologies and the larger number of operations available for each machine. Based on this classification, this paper focuses on the macro process planning, i.e. the selection of machines, working configurations and required tools.

To address the IPPS problem in reconfigurable manufacturing environment, several approaches are developed in recent years. Mohapatra *et al.* (2013) proposed an adapted version of the NGSA-II algorithm focusing on configuration setup planning and considering an adaptive process plan. The approach is guided by three objectives, i.e. the minimization of cost, the minimization of makespan and the maximization of the machine utilization. Bensmaine *et al.* (2014) presented a heuristic method for operation/machine sequential assignment. The assignment is driven by two indices based on machine availability. Touzout *et al.* (2018) proposed a hybrid multi-objective approach, combining the strengths of multi-objective integer linear programming (MOILP) to the evolutionary archived multi-objective simulated-annealing (AMOSA) algorithm to solve a sustainable process plan generation while considering greenhouse gas (GHG) emissions as objective function. In the same context, Touzout and Benyoucef(2018) presented a comparison between three different meta-heuristics as extension of their previous work (Touzout *et al.*2018). The first approach, called repetitive single-unit process plan metaheuristic (RSUPP), starts from an iterative MOILP (I-MOILP)to optimally solve the single-unit case and to get the optimal Pareto front (or a near-optimal front through AMOSA).The second approach is called iterated local search on single-unit process (ILSSUPP).Similarly, to the previous one, it generates an optimal or near-optimal Pareto front for single-unit process plan and, then, it combines several of them to produce the multi-unit process plan. The third approach, called archive-based iterated local search (ABILS), starts from ILSSUPP and RSUPP solution archives to generate the optimal Pareto front leading to better solutions or to enlarge the size of the Pareto front. Recently, Lee and Ha (2019) developed a single-objective approach for sustainable IPPS optimization introducing a new integrated representation of chromosome for genetic algorithm (GA) containing the operation attributes required for scheduling.

Evidences from the literature review show that on one hand, the product quality is crucial in manufacturing and not always considered in the design of a reconfigurable environment. On the other hand, IPPS problem is very promising but, to the best of our knowledge, rarely treated within reconfigurable contexts. To tackle these lacks, this paper considers simultaneously the product quality and the IPPS problem within the design of a RMS. A MOILP formulation of the IPPS problem including product quality considerations is presented together with a heuristic approach to design a sequential operation assignment criterion while considering alternative solutions and their resultant losses. The overall approach is guided by two objectives, i.e. the processing time (PT) representing the time required to perform all the operations and exploitation time (ET) that quantifies the overall machine utilization. The final goal is to achieve a balanced assignment of operations to the working machines.

3. PROBLEM DESCRIPTION AND FORMULATION

3.1 Problem description

Parts, resources and working machines are the key elements in the production system. Part manufacturing is according to its work cycle made of an operation sequence. Each operation requires a specific set of resources. Operation sequences are defined according to a precedence graph (Fig. 1) further describing the process requirements in terms of operations.

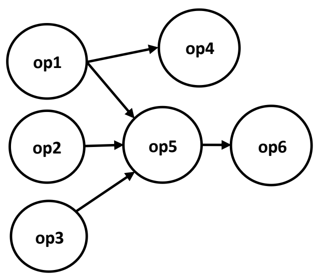

Fig. 1Example of precedence graph

In a reconfigurable manufacturing environment, each machine admits a certain number of configurations and a set of compatible tools. Consequently, to complete each operation one or more alternative triplets (machine-configuration-tool) is necessary. Figure 2 shows some examples of triplets.

Operation	Triplet	Machine	Configuration	Tool
op1	Γ1	M1	C2	T3
	Γ2	M2	C1	T3
op2	Γ3	M2	C2	T1
	Γ4	M3	C1	T4
	Γ5	M3	C2	T5
op3	Γ6	M2	C3	T3
op4	Γ7	M1	C1	T4
	Γ8	M2	C1	T1
	Γ9	M3	C2	T3
op5	Γ10	M1	C3	T2
	Γ11	M3	C1	T1
op6	Γ12	M2	C2	T5

Fig. 2 Example of triplets

The aim of an IPPS is to find the best assignment of operation sequences of multiple parts to the available resources, i.e. machines, optimizing one or more performance, e.g. cost, time, etc. Because of each part has the same precedence graph but different available sequences, within a multi-part scenario the number of alternative sequences grows significantly. Moreover, in reconfigurable manufacturing environment, the operation-triplet assignment increases substantially the complexity of the process plan generation making scheduling even harder due to conflicts on resources.

Section 3.2presents a multi-objective multi-part mathematical model minimizing PT and ET. As introduced, PT represents the total time required to perform all the operations of the part work cycle, including machine settings. ET refers to the total machine utilization. Because the process quality is affected by the wear of machines and tools, defect frequencies are considered to meet quality standard. As a function of time, the overall number of defects decreases thanks to a balanced assignment imposed by the two objective functions.

3.2 Mathematical formulation

The following notations are introduced.

Indices

i index for operations, $i = 1, \dots, O_p$
j, j' indices for machines, $j, j' = 1, \dots, M$
k, k' indices for configurations, $k, k' = 1, \dots, K$
p index for parts, $p = 1, \dots, P$
q index for positions in machine queue, $q = 1, \dots, Q$
t, t' indices for tools, $t, t' = 1, \dots, T$
γ index for triplets, with $\gamma(j, k, t)$,$\gamma = 1, \dots, \Gamma$

Parameters

$cct_{kk'}$ configuration changing time from k to k' [min]
$mct_{jj'}$machine changing time from j to j' [min]
$ot_{i\gamma}$ processing time for operation i with triplet γ[min]
$tct_{tt'}$ tool changing time from t to t' [min]
Ψ_{pi} set of predecessors for operation i of part p
ω_j defect rate for machine j [defect/min]
Ω quality level [defects]

Variables

$x_{pi\gamma}$ 1 if operation i of part p is processed by triplet γ, 0 otherwise
x_{pijq} 1 if operation i of part p is processed in position q by machine j, 0 otherwise
$y_{pijj'}$ 1 if operation i of part p, processed by machine j, follows a previous operation processed by machine j' 0 otherwise
$z_{jqk'k}$ 1 if machine $j$for operation in position q, needs a reconfiguration from k' to$k$, 0 otherwise
$z_{jqt't}$ 1 if machine $j$for operation in position q, needs a tool change from t' to$t$, 0 otherwise

Objective functions

The proposed model minimizes two objectives (1) and (2).

$$PT = \sum_{p=1}^{P} \sum_{i=1}^{O_p} \sum_{\gamma=1}^{\Gamma} x_{pi\gamma} \cdot ot_{i\gamma} + \sum_{p=1}^{P} \sum_{i=1}^{O_p} \sum_{j=1}^{M} \sum_{j'=1}^{M/\{j\}} y_{pijj'} \cdot mct_{jj'} + \sum_{j=1}^{M} \sum_{q=1}^{Q} \sum_{k=1}^{K} \sum_{k'=1}^{K/\{k\}} z_{jqk'k} \cdot cct_{k'k} + \sum_{j=1}^{M} \sum_{q=1}^{Q} \sum_{t=1}^{T} \sum_{t'=1}^{T/\{t\}} z_{jqt't} \cdot tct_{t't} \quad (1)$$

$$ET = \max_j \{ET_j\} \quad (2)$$

$$ET_j = \sum_{p=1}^{P}\sum_{i=1}^{O_p}\sum_{q=1}^{Q} x_{pijq} \cdot ot_{i\gamma} + \sum_{q=1}^{Q}\sum_{k=1}^{K}\sum_{k'=1}^{K/\{k\}} z_{jqk'k} \cdot cct_{k'k} + \sum_{q=1}^{Q}\sum_{t=1}^{T}\sum_{t'=1}^{T/\{t\}} z_{jqt't} \cdot tct_{t't}$$

PT is computed as the sum of the operation processing time, the time required to move a part from a machine to another, the configuration and tool changing time. On the other hand, ET_j, computed for each machine, considers the operation processing time, the configuration and tool changing time. The minimization of the maximum ET_j value leads to a balanced assignment.

Feasibility constraints

$$\min\{PT, ET\} \tag{3}$$

$$\sum_{j=1}^{M} ET_j \cdot \omega_j \leq \Omega \tag{4}$$

$$\sum_{\gamma=1}^{\Gamma} x_{pi\gamma} = 1 \quad \forall\, p, i \tag{5}$$

$$\sum_{i' \in \Psi_{pi}}\sum_{\gamma=1}^{\Gamma} x_{pi'\gamma} = |\Psi_{pi}| \quad \forall\, p, i \tag{6}$$

$$\sum_{q=1}^{Q} x_{pijq} = \sum_{\gamma \in \{\Gamma\}: j \in \gamma} x_{pi\gamma} \quad \forall\, p, i, j \tag{7}$$

$$x_{pijq} \leq \sum_{i'=1}^{O_p} x_{pijq-1} \quad \forall\, p, i, j, q \tag{8}$$

$$y_{pijj'} \leq \sum_{q=1}^{Q} x_{pijq} \quad \forall\, p, i, j, j' \tag{9}$$

$$y_{pijj'} \geq \sum_{q=1}^{Q} x_{pi-1jq} \quad \forall\, p, i, j, j' \tag{10}$$

$$z_{jqk'k} \leq 1 - \sum_{p=1}^{P}\sum_{i=1}^{O_p}\Big(x_{pijq} - \sum_{\gamma \in \Gamma:(j,k) \in \gamma} x_{pi\gamma}\Big) \quad \forall\, p, i, k, k' \tag{11}$$

$$z_{jqk'k} \geq 1 - \sum_{p=1}^{P}\sum_{i=1}^{O_p}\Big(x_{pijq-1} - \sum_{\gamma \in \Gamma:(j,k') \in \gamma} x_{pi\gamma}\Big) \quad \forall\, p, i, k, k' \tag{12}$$

$$z_{jqt't} \leq 1 - \sum_{p=1}^{P}\sum_{i=1}^{O_p}\Big(x_{pijq} - \sum_{\gamma \in \Gamma:(j,t) \in \gamma} x_{pi\gamma}\Big) \quad \forall\, p, i, t, t' \tag{13}$$

$$z_{jqt't} \geq 1 - \sum_{p=1}^{P}\sum_{i=1}^{O_p}\Big(x_{pijq-1} - \sum_{\gamma \in \Gamma:(j,t') \in \gamma} x_{pi\gamma}\Big) \quad \forall\, p, i, t, t' \tag{14}$$

$$x_{pi\gamma}, x_{pijq}, y_{pijj'}, z_{jqk'k}, z_{jqt't} \in \{0,1\} \tag{15}$$

Equation (3) minimizes the two objective functions, Equation (4) ensures that part defects meet the quality level. Equation (5) guarantees that each operation is assigned to only one triplet, while Equation (6) states that an operation can be assigned if all its predecessors are previously assigned. Equation (7) forces each assigned operation to occupy only one position in the queue. Equation (8) ensures that machine positions are progressively occupied, while Equations (9)-(10), (11)-(12) and (13)-(14) force to account, for each couple of subsequent operations, the machine changing time, configuration changing time and tool changing time. Finally, Equation (15) considers the variable domains.

4. PROPOSED APPROACH

The scheduling problem is NP-hard in nature due to its large solutions space. Exact methods cannot generate optimal solutions in reasonable time. In IPPS case, the solution space is even larger. Consequently, methods such as meta-heuristics are required to solve it. In this paper, extending Bensmaine *et al.* (2014) work, a novel heuristic approach for sequential assignment is proposed and applied.

Sequential assignment methods often do not consider effects of each local solution on the final result, i.e. the local best assignment can lead to a bad assignment in following steps. As a result, it may occur an overload on a specific machine and consequently bottleneck situations. Bensmaine *et al.* (2014) introduced a selection index (SI)related to machine availability. Within this new approach, two features are introduced. The former refers to the loss due to the worst-case assignment; the latter refers to the following operations in the precedence graph, i.e. the remaining unlocked operations to schedule with respect to the precedence graph. Thanks to the overlook on final solution, the global assignment is characterized by a balanced machine exploitation time. The proposed approach selects at each step the best assignment by means of computing the quality index. An overview on how the approach works is given in Fig. 3.

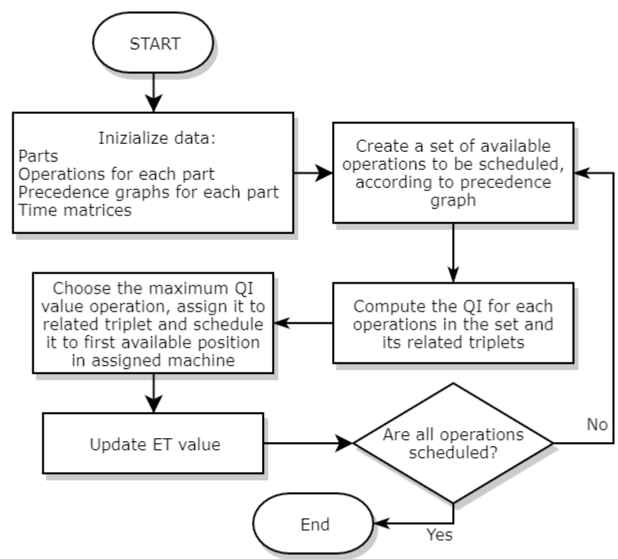

Fig. 3 Flow chart of the proposed approach

$$QI_{pi\gamma} = 1 - \frac{PT_{pi\gamma}}{\max\limits_{i}\{PT_{pi\gamma}\} + \frac{GAP_i + AVG_{i+}}{\Gamma_i}} \tag{16}$$

where

$$PT_{pi\gamma} = ET_{j:j\in\gamma} + ot_{i\gamma} \tag{17}$$

$$GAP_i = \max_{i}\{PT_{pi\gamma}\} - \min_{i}\{PT_{pi\gamma}\} \tag{18}$$

$$AVG_{i^+} = \text{avg operation time of following operations} \quad (19)$$

$$\Gamma_i = \text{\# available triplets for operation } i \quad (20)$$

The quality index (QI) in Equation (16) is computed for each operation to be scheduled. $PT_{i\gamma}$ in Equation (17) is the sum of the exploitation time of the related machine in Equation (3) and the operation processing time. GAP_i in Equation (18) represents the difference between the best-case and worst-case assignment. If we consider two operations, subject to the same conditions, the GAP_i factor prioritizes the one with a bigger loss in the worst-case assignment. Using the factor in Equation (19), the QI value is larger for operations that are predecessors. Finally, the factor in Equation (20) considers the number of alternative assignments. The greater the number of alternatives, the lower the machine overload risk is with low urgency to schedule the operation; thus, the QI value decreases.

Figure 4 illustrates the pseudo-code of the proposed algorithm.

```
Algorithm
1. Initialize input data
2. while (n° of scheduled operations < tot. n° of operations)
3.   create the set of available operations
4.   compute QI for each operation in the set
5.   schedule the maximum QI value operation
6.   update ET
7. end while
8. return scheduling
```

Fig. 4 Algorithm

The first step consists of building the set of available operations to be scheduled. The QI is computed for each operation in the set, then the operation with the larger QI value is scheduled. The QI considers alternative assignments (Γ_i), the loss due to the worst assignment (GAP_{i}) and unlockable operations (AVG_{i^+}).

The proposed approach guarantees a balanced assignment selecting, at each step, the most available machine while considering the following operations as well. A balanced assignment is related to the output quality due to the tool usury and the machine defects frequency.

5. ILLUSTRATIVE NUMERICAL EXAMPLE

The following illustrative numerical example applies the proposed approach. Several instances with different number of parts and different set of operations per parts are focused. Operations and related triplets are generated randomly starting from a given number of machines, configurations and tools. Figure5 shows the key data of the seven instances.

The heuristic is coded in Java environment by the definition of different classes for each entity, e.g. parts, operations, machines, configurations, etc. The result of the run is the scheduling of operations and their assignment to machines with related triplets and starting time. An example of scheduling is in Fig.6.

Instances	n° of Parts	n° of Operations	n° of Machines	n° Configurations	n° Tools
Inst 1	2	5, 7	3	3,3,2	5,1,3
Inst 2	2	5, 10	3	3,2,3	5,5,4
Inst 3	2	8, 10	3	2,3,1	9,5,7
Inst 4	3	8, 10, 6	3	4,2,3	4,8,9
Inst 5	2	9, 13	4	4,4,2,3	9,6,4,7
Inst 6	3	7, 5, 10	4	2,5,3,4	6,2,7,8
Inst 7	3	12, 15, 8	4	3,5,4,4	8,6,9,4

Fig. 5Used instances

OP	p2o3	p3o2	p1o5	p3o3	p1o1	p3o11	p2o6	p1o14
Time	0	0	0	13,81	15,57	11,82	22,62	27,25
Machine	M1	M2	M3	M2	M1	M3	M3	M2
Configuration	C1	C1	C1	C2	C3	C1	C2	C1
Tool	T3	T1	T3	T5	T2	T4	T3	T4

Fig. 6Example of IPPS

The same instances are used in an adapted approach from Bensmaine *et al.* (2014). The comparison, shown in Fig. 7, is based on two indicators: the makespan that refers to the maximum machine exploitation time value, and the GAP that computes the difference between the maximum and minimum machine exploitation time.

	Quality index		Selection index		QI/SI	
Instances	Makespan	GAP	Makespan	GAP	Makespan	GAP
Inst 1	74,58	12,98	87,28	33,35	14,6%	61,1%
Inst 2	81,43	10,49	87,07	16,78	6,5%	37,5%
Inst 3	141,39	46,07	144,86	74,34	2,4%	38,0%
Inst 4	179,65	26,21	183,49	33,78	2,1%	22,4%
Inst 5	144,84	12,42	156,22	49,16	7,3%	74,7%
Inst 6	133,96	42,21	143,34	56,9	6,5%	25,8%
Inst 7	205,5	79,59	231,02	106,32	11,0%	25,1%

Fig. 7 Results

Results highlight improvements in terms of makespan and the correspondent effect on machine exploitation time. The decreased value of makespan leads to an increased values of exploitation time on other machines.

6. CONCLUSIONS AND PERSPECTIVES

In this paper, a new heuristic for the integrated process planning and scheduling (IPPS) problem in reconfigurable environment is presented. The purpose is to get the best assignment and scheduling criteria that considers the process quality constraints. Quality considerations deal with machine and tool usury rate, which are computed as a function of time. Because of sequential assignment methods lack an overview on the system, the choice of step-by-step local solution is crucial for a successful result. The strength of the proposed approach lies in the fact that, at each step, the assignment choice is based on its effects. Consequences of each available assignment are measured by means of an index computation, which drives the local solution choice. After defining the problem and its mathematical formulation, a heuristic approach is outlined and compared to an existing method. The comparison shows good improvements. Results fit properly with the model objective functions, but a metaheuristic is required to solve it (sub) optimally.

In further works, metaheuristic implementations and comparisons are expected. Moreover, to move towards sustainable manufacturing, the integration of different sustainable metrics, e.g. energy consumption, carbon footprint, etc., to the IPPS problem is possible. The idea is to consider sustainability metrics as guideline objectives for process planning and scheduling in multiple contexts, such as dynamic, stochastic and smart manufacturing.

7. REFERENCES

Bensmaine A., Dahane M., Benyoucef L., (2014), A new heuristic for integrated process planning and scheduling in reconfigurable manufacturing systems, *International Journal of Production Research*, 52:12, 3583-3594.

Chen, Q., and B. Khoshnevis, (1990), Integration of Process Planning and Scheduling Functions, *Journal of Intelligent Manufacturing*, 1, 165–176.

ElMaraghy, H.A., (2005), Flexible and reconfigurable manufacturing systems paradigms, *Flexible Services and Manufacturing Journal*, 17, 266.

ElMaraghy, H.A., (2007), Reconfigurable process plans for responsive manufacturing systems, Digital Enterprise Technology, 35-44.

Kim Y.K., Park K., Ko J., (2003), A symbiotic evolutionary algorithm for the integration of process planning and job shop scheduling, *Computer & Operational Research*, 30, 1151–1171.

Koren, Y., Heisel, U., Jovane F., Moriwaki T., Pritschow G., Ulsoy G., Van Brussel H., (1999), Reconfigurable manufacturing systems. *CIRP Annals - Manufacturing Technology*, 48/2, 527-540.

Lee H. C. and Ha C. (2019), Sustainable Integrated Process Planning and Scheduling Optimization Using a Genetic Algorithm with an Integrated Chromosome Representation, *Sustainability*, 11, 502.

Marri H.B., Gunasekaran A. and Grieve R. J.,(1998),Computer-aided Process Planning: A State of Art, *The International Journal of Advanced Manufacturing Technology*, 14, 261-268.

Mohapatra P., Benyoucef L., Tiwari M. K., (2013), Integration of process planning and scheduling through adaptive setup planning: a multi-objective approach, *International Journal of Production Research*, 51, 23-24.

Salvendy, G. (2001), Handbook of Industrial Engineering: Technology and Operations Management. 3rd ed. Hoboken, NJ: JohnWiley & Sons.

Touzout F.A., Benyoucef L., Benderbal H. H., Dahane M.,(2018), A hybrid multi-objective based approach for sustainable process plan generation in a reconfigurable manufacturing environment, *IEEE International Conference on Industrial Informatics* (INDIN), 16, 343-348.

Touzout F.A and Benyoucef L. (2018), Sustainable multi-unit process plan generation in a reconfigurable manufacturing environment: A comparative study of three hybrid-meta-heuristics, IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), 23, 661-668.