Sustainable reconfigurable manufacturing system design using adapted multi-objective evolutionary-based approaches

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Abstract
Nowadays, manufacturing systems should be cost-effective and environmentally harmless to cope with various challenges in today’s competitive markets. This paper aims to solve an environmental-oriented multi-objective reconfigurable manufacturing system design (i.e., sustainable reconfigurable machines and tools selection) in the case of a single-unit process plan generation. A non-linear multi-objective integer program (NL-MOIP) is presented first, where four objectives are minimized respectively, the total production cost, the total production time, the amount of the greenhouse gases emitted by machines, and the hazardous liquid wastes. Second, to solve the problem, we propose four adapted versions of evolutionary approaches, namely two versions of the well-known non-dominated sorting genetic algorithm (NSGA-II and NSGA-III), weighted genetic algorithms (WGA), and random weighted genetic algorithms (RWGA). To show the efficiency of the four approaches, several instances of the problem are experimented, and the obtained results are analyzed using three metrics respectively hypervolume, spacing metric, and cardinality of the mixed Pareto fronts. Moreover, the influences of the probabilities of genetic operators (crossover and mutation) on the convergence of the adapted NSGA-III are analyzed. Finally, the TOPSIS method is used to help the decision-maker ranking and select the best process plans.

Keywords Reconfigurable manufacturing system · Sustainability · Greenhouse gases · Liquid hazardous wastes · Multi-objective optimization · NSGA-III · Hypervolume metric · Spacing metric

1 Introduction
Nowadays, manufacturing enters a new context in which all manufacturers must compete in a global environment. As a result, global competition improves the selectivity of the customers, which drives the introduction of new products and causes significant changes in products demands. Customer satisfaction is the main task for most companies.

To stay competitive, manufacturers must use systems that not only produce at a high production rate, allowing rapid and cost-effective response to market changes, but also environmentally harmless. Therefore, manufacturers are moving towards a recent concept of production able to rapidly change in its structure (hardware and software items).

Reconfigurable manufacturing system (RMS) is a novel paradigm designed at the outset for rapid change in structure, as well as in hardware and software components, to quickly adjust production capacity and functionality within a part family in response to sudden changes in the market or in regulatory requirements [1]. According to [2], “RMS is designed to combine the high flexibility of flexible manufacturing system (FMS) with the high production rate of dedicated manufacturing system (DMS).” It is achieved by designing the system according to two principles [3–5]: (i) Design the system and its machines for a flexible structure that enables system scalability in response to market demands and system/machine adaptability to new products. The structure may be adjusted at the system level (e.g., adding machines) and at the machine level (e.g.,
changing machine hardware and control software). This reduces the system time. (ii) Design the system around the part family, with the customized flexibility required for producing all parts of this part family. This reduces the system cost.

More and more, companies are considering sustainability as an essential factor. Statistics have shown that the greenhouse gases (GHG) emitted from the use of energy sources such as electricity, coal, oil, and gas during manufacturing accounts for over 37%, even 50%, of the total GHG worldwide (“https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions”, “https://www.epa.gov/ghgemissions”). Therefore, companies have started to take measures to reduce GHG emissions from their products and services. The U.S. Department of Commerce defines sustainable manufacturing as the “creation of manufactured products using processes that minimize negative environmental impacts, conserve energy and natural resources, are safe for employees, communities and consumers” [6]. More recently, RMS is thought to be one of the most suitable paradigms with sustainability requirements. Battaia et al. [7] and Touzout et al. [8] addressed how RMS can be connected to sustainable manufacturing from the point of view of sustainability production. Manufacturing processes and manufacturing activities are also classified as major sources of greenhouse gas (GHG) emissions.

This paper addresses an environmental-oriented multi-objective RMS design problem (i.e., sustainable reconfigurable machines and tools selection). More specifically:

1. A non-linear multi-objective integer program (NLMOIP) is presented in the case of a single-unit process plan generation.
2. Four objectives are minimized respectively, the total production cost, the total production time, the amount of the greenhouse gases emitted by machines and the hazardous liquid wastes.
3. To solve the problem, adapted versions of the weighted genetic algorithm (WGA), random weighted genetic algorithm (RWGA), and the well-known non-dominated sorting genetic algorithm, respectively (NSGA-II) and (NSGA-III) are presented.
4. To illustrate the comparisons between the four approaches, rich experimental results are presented and analyzed using three metrics respectively hypervolume, spacing metric, and cardinality of the mixed Pareto fronts.
5. The influences of the probabilities of genetic operators (crossover and mutation) on the convergence of the adapted NSGA-III are analyzed, and the TOPSIS method is used to help the decision-maker ranking and select the best process plans.

The rest of the paper is organized as follows: Section 2 reviews some research works dedicated to reconfigurable manufacturing problems, including process plan generation and sustainability issues. Section 3 describes the problem under consideration and its mathematical formulation. Section 4 details the four adapted evolutionary approaches, namely, WGA, RWGA, NSGA-II, and NSGA-III. Section 5 presents and analyses some experimental results. Finally, Section 6 concludes the paper with some future work directions.

2 Literature review

Reconfigurable manufacturing system is one of the latest manufacturing paradigms. RMS offers new aspects and faces many new challenges. These possibilities make RMS a very active research field [9–11]. Nevertheless, in this section, we briefly review some research works dedicated to RMS design problems, sustainability and manufacturing, and sustainability in RMS.

2.1 Reconfigurable manufacturing system design

According to [12], “RMS is a system where machines, machine components as well as the handling system can be added, modified, deleted or exchanged, integrated new technology according to production requirements to react faster to the constant evolution, unexpected demand for products and to the variety of products.” ElMaraghy [13] argued that “changes and evolutions of manufacturing systems as well as products need to be related to reconfiguration and reconfigurable process planning.” Goyal et al. [14] defined the reconfigurability as: “the ability of a manufacturing system to easily and cost-effectively changes and reorients its components frequently, to attain the objectives.” The process planning (called also process plan generation) is defined by [15] as “a preparatory step before manufacturing, which determines the sequence of operations or processes needed to produce a part or an assembly.”

Musharavati and Hamouda [16] investigated the use of simulated annealing-based algorithms in solving process planning problem for a RMS. Chaube et al. [17] and Bensmaine et al. [18] integrated the cost- and time-efficient problem of process plan generation using the adapted non-dominated sorting genetic algorithm (NSGA-II). They elaborated rich experimental comparisons and analyses based on the obtained Pareto fronts. Hasan and Jain [19] introduced a method that can be modified for optimal selection of machine configurations across stages for a serial reconfigurable product flow line. Bensmaine et al. [18] adapted a
multi-objective based method for a reconfigurable manufacturing system design, which consists of selecting a subset of machines from a set of possible candidate machines to operate a set of operations needed to manufacture a given product. Haddou-Benderbal et al. [20] discussed machines unavailability in RMS by developing a new hybrid heuristic to minimize the impact of perturbations caused by the eventual unavailability of selected machines on the system. Wang et al. [21] developed quantitative index models that reflect the essential characteristics of an RMS (scalability, convertibility, diagnosability, modularity, integrability, and customization) and rank alternative reconfiguration schemes, which possess both advantages and disadvantages. The authors used an integrated AHP method and a two-phase PROMETHEE method to evaluate the alternatives comprehensively. Recently, [22] developed an adapted version of the AMOSA based on modularity to solve the integrated design and process plan generation problem for RMS. Moreover, [23] considered the relations, which link the designed system with two critical issues: its logical environment, i.e., the product family in which the RMS can evolve, and its physical environment, i.e., the physical work shop that implements the RMS. A two-phase based-AMOSA approach is developed to determine the best machine layout for all the selected machines of the product family.

Recently, [24] developed a systematic methodology for setting modules of reconfigurable manufacturing tools (RMTs). Starting with a classification of conceptual modules, the methodology allows creating a functional module group of RTMs following structural and functional characteristics of the components that construct the machine tools, the geometry modules, and the basic structure modules. Touzout and Benyoucef [25] proposed and compared three hybrid heuristics, namely, repetitive single-unit process plan heuristic (RSUPP), iterated local search on single-unit process plans heuristic (LSSUPP), and archive-based iterated local search heuristic (ABILS), to solve the multi-unit process plan generation problem in RMS, taking into consideration the minimization of the maximum machines exploitation time and the classical total production cost and the total completion time. Battaïa et al. [26] addressed a cost optimization problem for flow lines with reconfigurable machines for batch production. A mixed-integer programming model is developed, taking into account constraints related to (i) design of machining modules, turrets, and machines, (ii) part locations, and (iii) precedence relations among operations. The objective is to minimize equipment cost while reaching a given output and satisfying all the constraints.

2.2 Sustainability and manufacturing

The sustainable production system is defined by [27] as “a system able to transform materials without (i) greenhouse gas emissions and (ii) use of unsustainable or toxic materials or (iii) produce waste”. Some research directions are identified, leading to solutions for sustainable manufacturing [28]. Jayal et al. [29] stated that achieving sustainability goes through optimizing not only the product or its manufacturing process but also the entire supply chain as a whole. Küster et al. [30] and Moon et al. [31] tried to integrate energy consumption into the total production cost using time of use (TOU) tariffs in scheduling problems. Choi and Xirouchakis [32] proposed a model that considers the environmental and energy consumption effects of capacity change in a reconfigurable and flexible production environment. Afrin et al. [33] attempted to minimize the greenhouse gases emitted during manufacturing for a production line with rotary transfer and turrets. They proposed a framework to investigate the environmental impact of greenhouse gas emitted and energy consumed by the system-level processes during the machining and non-machining operations. Huang and Badurdeen [34] presented a metrics-based methodology for an enterprise sustainability index (EnSI). The EnSI evaluates sustainable manufacturing performance at the enterprise level.

More recently, a quantitative framework is proposed by [35] for sustainable manufacturing. The authors described its application to the automotive industry and demonstrated that material alternatives could enhance sustainability objectives. Zhu et al. [36] published a comprehensive literature review dedicated to the used modeling techniques to address the sustainable food supply chain (SFSC) issues. The authors studied the main challenges that emerge from modeling sustainability. Furthermore, to identify how sustainable manufacturing research contributes to the development of the Industry 4.0 agenda, [28] proposed a conceptual framework formed by the principles and technological pillars of Industry 4.0, sustainable manufacturing scope, and sustainability dimensions. They concluded that “the field is legitimated but not consolidated, however, it is evolving based on the development of new business models and value-creation-chains integration. Moreover, research gaps and opportunities for field development, becoming more mature and having a significant contribution to fully developing the agenda of Industry 4.0”.

2.3 Sustainability and RMS

Zhang et al. [37] addressed the problem of formal modeling and verification of reconfigurable and energy-efficient
manufacturing systems (REMSs) that are considered as reconfigurable discrete event control systems. They took advantage of dynamic reconfigurations of machines of a RMS between their working modes and energy-efficient modes to reduce system energy consumption. Ghanei and AlGeddawy [38] developed a new linear mixed-integer mathematical model to maximize the sustainability of changeable manufacturing systems based on the daily varying energy pricing. The model considers three main factors that affect system sustainability, namely (1) the changing pattern in energy prices throughout the day, (2) the transportation cost of jobs between machines, which depends on machines locations in the system, and (3) the setup cost of each machine, which is dependent on the job sequence. The model output is a system configuration plan, indicating the arrangement of machines in the system and the sequence of jobs that need to be produced on that day.

Recently, [8] considered the sustainable multi-objective single-unit process plan generation in a reconfigurable manufacturing environment, where the amount of greenhouse gases (GHG) emitted during the production process is minimized in addition to manufacturing criteria such as cost and time. They developed an iterative multi-objective integer linear programming (I-MOILP) and adapted NSGA-II and the archived multi-objective simulated-annealing (AMOSA) to solve the problem. Furthermore, they studied the influence of the probabilities of genetic operators on the convergence of the adapted NSGA-II. Furthermore, [39] developed a non-linear mathematical model to optimize the energy consumption in an RMS by redefining two of its core characteristics, namely modularity and integrability. The model minimizes the system’s total energy consumption by selecting the most suitable modular machines from a set of reconfigurable candidate machines. The optimization problem is addressed using an exhaustive search heuristic algorithm and demonstrated through simple illustrative numerical examples. Battaïa et al. [7] showed how the RMS’s concepts could lead to the design of sustainable and energy-efficient manufacturing systems. Two questions are considered: how to increase the life cycle of a RMS (including how to use their components optimally after the end of life)? and how to decrease the emissions and energy consumption during the life cycle? They concluded that both questions should be analyzed at the RMS design stage, and an intelligent choice of technologies and modules to use could be a solution to these problems.

From the above literature review, we can see that RMS is a very active research topic, and significant progress has been made. Nevertheless, few research works are dedicated to sustainable RMS problems in general and sustainable RMS design particularly. Therefore, in this paper, from one hand, we aim to highlight the importance of designing sustainable reconfigurable manufacturing systems. On the other hand, and to tackle the lack of works in this area, we propose to adopt four evolutionary approaches, respectively, WGA, RWGA, NSGA-II, and NSGA-III, to solve the sustainable reconfigurable machines and tools selection problem. Rich experimental results are presented and analyzed using three metrics showing the superiority of NSGA-III.

3 Problem description and formulation

In the following, we describe more in details the problem under consideration and present its mathematical formulation.

3.1 Problem description

Let us consider a single unit of a product to be manufactured in a reconfigurable environment. The product is defined by a set of features to be achieved. Each feature requests a set of operations linked by precedence constraints, as illustrated in Fig. 1. From the example, we can see that we have four features: $F_1 = \{O_{P_1}\}$, $F_2 = \{O_{P_2}, O_{P_3}\}$, $F_3 = \{O_{P_4}, O_{P_5}, O_{P_6}\}$ and $F_4 = \{O_{P_7}\}$. Moreover, three key data define an operation: the precedence constraints, the set

![Fig. 1 An illustrative product schema and operations precedence graph](Image)
of candidate tools and the tool approach directions (TADs) (i.e., \( \pm x, \pm y, \pm z\)). Table 1 shows the required TADs and tools for the operations of our example.

Once the requirements of the operation are identified, a machine can perform a certain number of operations. Given that, for each machine, the sets of available configurations and compatible tools are identified. Thus, each operation \( OP_i \) requires an association of machine-configuration-tool \( (M, C, T) \) called triplet \( TO_i \). Table 2 presents the TADs, configurations and tools that each machine can offer.

The process plan generation consists of sequencing the operations to be performed on the machines (under machines configurations, used tools, and precedence graph constraints) and the triplets to perform each operation in the sequence. Table 3 presents a simple generated process plan of our example.

In the following, the generated process plans should satisfy the manufacturing requirements with respect to manufacturing criteria, respectively, total production cost and the total completion time. Moreover, the sustainability criteria cover both the greenhouse gases (GHG) emissions and the liquid hazardous wastes. To summarize, four criteria are minimized in this study:

1. The total production cost: It comprises the cost of changing machines, configurations, tools and the cost of processing, cost of the emitted greenhouse gases and cost of the hazardous liquid waste.
2. The total production time: It consists of the engaged time in changing machines, configurations, tools, and the processing time of the operations.
3. The waste: It comprises the hazardous liquid waste during processing of the operations, including:
   - wastes oils/water, hydrocarbons/water mixtures, emulsions;
   - wastes from the production, formulation, and use of resins, latex, plasticizers, glues/adhesives;
   - wastes resulting from surface treatment of metals and plastics;
   - residues arising from industrial waste disposal operations.

### Table 1 Operations requirements

| OP | TAD | Tools |
|----|-----|-------|
|    | +X  | +Y  | +Z  | -X  | -Y  | -Z  |       |
| \( OP_1 \) | x   | x   | x   | x   |     |     | T2    |
| \( OP_2 \) | x   |     |     |     | x   |     | T3    |
| \( OP_3 \) |     | x   |     |     |     |     | T1    |
| \( OP_4 \) | x   | x   |     |     | x   |     | T1    |
| \( OP_5 \) |     |     | x   |     |     | x   | T3    |
| \( OP_6 \) | x   | x   |     |     |     | x   | T2    |
| \( OP_7 \) |     |     | x   |     |     | x   | T3    |

### Table 2 Machines requirements

| Ms | Cs | TAD | Tools |
|----|----|-----|-------|
|    |    | +X  | +Y  | +Z  | -X  | -Y  | -Z  |       |
| \( M_1 \) | C_1 | x   |     |     |     |     |     | T2,T3 |
|          | C_2 |     |     |     | x   |     |     |       |
| \( M_2 \) | C_1 | x   | x   |     |     |     |     | T1,T3 |
|          | C_2 |     |     |     | x   |     |     |       |
|          | C_3 |     |     |     |     |     | x   |       |
| \( M_3 \) | C_1 | x   | x   | x   | x   |     |     | T1,T2 |
| \( M_4 \) | C_1 |     | x   | x   |     |     |     | T1,T2 |
|          | C_2 |     |     | x   | x   |     |     |       |
| \( M_5 \) | C_1 |     | x   | x   | x   |     |     | T3    |
Table 3 Illustrative structure of a process plan

| Operation | OP1 | OP3 | OP4 | OP2 | OP6 | OP5 | OP7 |
|-----------|-----|-----|-----|-----|-----|-----|-----|
| Machine   | M3  | M4  | M2  | M1  | M4  | M2  | M2  |
| Configuration | C1  | C1  | C1  | C2  | C2  | C2  | C3  |
| Tool      | T2  | T1  | T1  | T3  | T2  | T3  | T3  |

4. The green house gases (GHG) emissions during the total production process.

3.2 Mathematical formulation

Parameters

- **n**: Number of operations
- **OP**: Set of operations
- **i, i’**: Index of operations
- **PRi**: Set of predecessors of operation **OPi**
- **m**: Number of machines
- **M**: Set of machines
- **j, j’**: Index of machines
- **G**: Set of greenhouse gases
- **g**: Index of greenhouse gases
- **L**: Available liquid
- **li,t**: Required liquid for operation **OPi** when using triplet **t** per time unit
- **EPi,t**: Estimated hazardous liquid waste for operation **OPi** when using triplet **t**
- **fef**: Emission factor for electricity consumption
- **fi,g**: Operation **OPi** emitting greenhouse gas type **g** per time unit
- **t, t’**: Index of triplets
- **TOi**: Set of available triplets for operation **OPi**
- **TMj**: Set of available triplets using machine **Mj**
- **T**: Set of triplets, where **T = TOi ∪ TMj**
- **c, c’**: Index of configurations
- **tl, tl’**: Index of tools
- **p, p’**: Index of positions in the sequence
- **GWPG**: Global warning potential for emitted greenhouse gas type **g**

Cost parameters

- **CCMJ,j’**: Machine changeover cost per time unit
- **CCCc,c’**: Configuration changeover cost per time unit
- **CCTil,t’l’**: Tool changeover cost per time unit
- **Pci,t**: Operation **OPi** processing cost when using triplet **t** per time unit
- **DCGHH**: Disposal cost of the emitted greenhouse gases
- **DCLHW**: Disposal cost of the hazardous liquid waste

Time parameters

- **TCMj,j’**: Machine changeover time
- **TCCc,c’**: Configuration changeover time
- **TCTil,t’l’**: Tool changeover time
- **Pci,t**: Operation **OPi** processing time when using triplet **t**

Energy parameters

- **ECMJ,j’**: Machine changeover energy per time unit
- **ECCc,c’**: Configuration changeover energy per time unit
- **ECTil,t’l’**: Tool changeover energy
- **Pci,t**: Operation **OPi** processing energy when using triplet **t** per time unit
- **IECj**: Initial energy consumption of machine **Mj**

Decision variables

The following decision variables are used:

\[ x_{i,p}^t = 1 \text{ if operation } OP_i \text{ is using triplet } t \text{ at the } p^{th} \text{ position}, 0 \text{ otherwise.} \]
\[ y_{m,p}^t = 1 \text{ if machine } M_j \text{ is using triplet } t \text{ at the } p^{th} \text{ position}, 0 \text{ otherwise.} \]
\[ MC_{p-1}^{p-1}(j, j’) = 1 \text{ if there has been a change from machine } M_j \text{ to machine } M_{j’} \text{ between positions } p - 1 \text{ and } p, 0 \text{ otherwise.} \]
\[ TC_{p-1}^{p-1}(t, t’) = 1 \text{ if there has been a change from triplet } t \text{ to triplet } t’ \text{ of machine } M_j \text{ between positions } p - 1 \text{ and } p, 0 \text{ otherwise.} \]

Objective functions

Our problem can be formulated as a non-linear multi-objective integer program (NL-MOIP), where four objectives are optimized:

1. The total production cost \( f_c \): Equation (1) represents the total production cost to be minimized. It includes the following costs: machine changeover cost, configuration changeover cost, tool changeover cost, processing cost, emitted greenhouse gases cost and...
The amount of hazardous liquid waste during the production

\[ f_{LC} = \sum_{p=1}^{n} \sum_{i=1}^{n} \sum_{t \in T_{Oi}} x_{i,p}^{t} \times P_{c,i,t} \times P_{t,i} \]

\[ + \sum_{p=2}^{n} \sum_{j=1}^{m} MC_{p}^{j-1}(j, j') \times CCM_{j,j'} \times TCM_{j,j'} \]

\[ + \sum_{p=2}^{n} \sum_{j=1}^{m} \sum_{t, t' \in T_{Mj}} TC_{j,p}^{j-1}(t, t') \times (CCT_{tl,tl'} \times TCT_{tl,tl'}) \]

\[ + (DC_{GHG} \times f_{GHG} + DC_{LWH} \times f_{LWH}) \] (1)

2. The total production time \( f_{p} \): Equation (2) calculates the total production time to be minimized. It includes the following times: machine changeover time, configuration changeover time, tool changeover time and processing time.

\[ f_{p} = \sum_{p=1}^{n} \sum_{i=1}^{n} \sum_{t \in T_{Oi}} x_{i,p}^{t} \times P_{t,i} \]

\[ + \sum_{p=2}^{n} \sum_{j=1}^{m} \sum_{t \in T_{Oj}} \sum_{t' \in T_{Mj}} MC_{p}^{j-1}(j, j') \times CCM_{j,j'} \times TCM_{j,j'} \]

\[ + \sum_{p=2}^{n} \sum_{j=1}^{m} \sum_{t, t' \in T_{Mj}} TC_{j,p}^{j-1}(t, t') \times (CCT_{tl,tl'} \times TCT_{tl,tl'}) \] (2)

3. The amount of hazardous liquid waste \( f_{LHW} \): Equation (3) defines the amount of hazardous liquid waste to be minimized.

\[ f_{LHW} = \sum_{p=1}^{n} \sum_{i=1}^{n} \sum_{t \in T_{Oi}} x_{i,p}^{t} \times P_{t,i,t} \times E_{P,i,t} \] (3)

4. The amount of greenhouse gases emitted \( f_{GHG} \): Equation (4) defines the amount of greenhouse gases emitted during the manufacturing process to be minimized. It is composed of two parts. The first considers the energy consumption taking into account the emission factor for consumed electricity. The second considers the emitted gases taking into account the factor of global warming potential (GWP). In this research work, GWP factor is used to convert emissions of the other greenhouse gases into \( CO_2 \) equivalents.

\[ f_{GHG} = f_{EC} \times f_{EC} + \sum_{p=1}^{n} \sum_{i=1}^{n} \sum_{t \in T_{Oi}} x_{i,p}^{t} \times P_{t,i,t} \times f_{EC} \times GW_{P,t} \] (4)

Equation (5) describes more in details how to compute the total energy consumption during the production \( f_{EC} \).

\[ f_{EC} = \sum_{p=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{m} y_{p,i}^{j} \times x_{i,p}^{j} \times I_{EC,j} \]

\[ + \sum_{p=1}^{n} \sum_{i=1}^{n} \sum_{t \in T_{Oi}} x_{i,p}^{t} \times P_{c,i,t} \times P_{t,i,t} \]

\[ + \sum_{p=2}^{n} \sum_{j=1}^{m} MC_{p}^{j-1}(j, j') \times CCM_{j,j'} \times TCM_{j,j'} \]

\[ + \sum_{p=2}^{n} \sum_{j=1}^{m} \sum_{t, t' \in T_{Mj}} TC_{j,p}^{j-1}(t, t') \times (CCT_{tl,tl'} \times TCT_{tl,tl'}) \]

\[ \times (TCC_{c,c'} \times TCT_{c,c'}) \] (5)

We can see that, \( f_{EC} \) is a non-linear function. In order to transform it to a linear one, we can use the following equations:

\[ y_{p,i}^{j} \times x_{i,p}^{j} = z \]

\[ S.t : z \leq x_{i,p}^{j} \]

\[ z \leq y_{p,i}^{j} \]

\[ z \geq y_{p,i}^{j} + x_{i,p}^{j} - 1 \]

\[ z \in [0, 1] \]

3.3 Model

The model is therefore represented as follows:

\[ \text{min}\ f_{LC} \]

\[ \text{min}\ f_{p} \]

\[ \text{min}\ f_{LHW} \]

\[ \text{min}\ f_{GHG} \]

\[ \sum_{i=1}^{n} \sum_{t \in T_{Oi}} x_{i,p}^{t} = 1 \quad \forall p = 1 \ldots n \] (6)

\[ \sum_{i=1}^{n} \sum_{t \in T_{Oi}} x_{i,p}^{t} = 1 \quad \forall i = 1 \ldots n \] (7)

\[ \sum_{t \in T_{Oi}} x_{i,p}^{t} \leq \sum_{p'=1}^{n} \sum_{t' \in T_{O'}} x_{i,p'}^{t'} \quad \forall i = 1 \ldots n, \forall p = 2 \ldots n \] (8)

\[ \sum_{j=1}^{m} \sum_{i \in T_{Mj}} y_{p,i}^{j} = 1 \quad \forall p = 1 \ldots n \] (9)

\[ y_{p,i}^{j} \geq x_{i,p}^{j} \quad \forall i = 1 \ldots n, \forall p = 1 \ldots n, \forall j = 1 \ldots m, \forall t \in T_{Mj} \] (10)

\[ \sum_{i=1}^{n} x_{i,p}^{t} + \sum_{i=1}^{n} x_{i,p}^{t-1} \leq MC_{p}^{j-1}(j, j') \]

\[ + 1 \quad \forall p = 2 \ldots n, \forall t, t' \in T \] (11)
\[ y_{j,p,t} + y_{j-1,t',t} \leq T_C^{j,p-1}(t, t') + 1 \forall p = 2 \ldots n, \forall j = 1 \ldots m, \forall t, t' \in TM_j \] (12)

\[ \sum_{t,t' \in TM_j} T_C^{j,p-1}(t, t') = 1 \forall p = 1 \ldots n, \forall j = 1 \ldots m \] (13)

\[ \sum_{p=1}^{n} \sum_{i=1}^{n} \sum_{t \in TO_i} x_{i,p}^j \times l_{i,t} \times P_{t,i,t} \leq L \] (14)

Constraint (6) states that one operation is processed at each position of the process plan. Constraint (7) states that each operation is processed only once. Constraint (8) considers that each operation should respect the predecessors’ operations. Constraint (9) represents that each machine can use only one configuration and one tool at once. Constraint (10) states that the requirement of configuration and tool in position \( p \) for \( m^{th} \) machine. Constraint (11) defines if there is a change of machine between position \((p - 1)\) and \((p)\). Constraint (12) defines if there is a change of configuration and/or tool between position \((p - 1)\) and \((p)\). Constraint (13) states that there is only one change of configuration and/or tool between position \((p - 1)\) and \((p)\). Constraint (14) represents the limited liquid storage of the manufacturer.

### 3.4 Complexity

In a reconfigurable manufacturing environment, the process plan generation problem is NP-hard. By eliminating the aspect, where for each operation, an optimal machine, configuration, and tool need to be designated and the precedence constraints, an instance from the well-known travelling salesman problem (TSP) can be reduced in a polynomial time to an instance of our problem. Hence, in this case, the operations will represent the nodes of the network, and the objective will be to find the optimal sequence (route) in terms of time or cost, where the time/cost from one node to another corresponds to the changeover-time/changeover-cost. Since the TSP is NP-hard, the problem addressed in this study is also NP-hard.

### 4 Proposed approaches

To generate optimal process plans for sustainable and classical manufacturing criteria, we attempt to use four meta-heuristic approaches, namely, non-dominated sorting genetic algorithm II (NSGA-II), non-dominated sorting genetic algorithm III (NSGA-III), weighted genetic algorithm (WGA), and random weighted genetic algorithm (RWGA). This section describes more in details the four used approaches.

#### 4.1 Solution representation and evaluation

To be able to manipulate the solutions (process plans in our case) and to obtain acceptable results using the adapted evolutionary approaches, each solution is represented in the form of a matrix with four rows (Operation, Machine, Configuration, and Tool) and \( n \) columns (number of operations) as the form shown in Table 3. It is interpreted from left to right, column by column. For example, the first column indicates that: the operation \( OP1 \) is executed by the machine \( M3 \), under the configuration \( C1 \), using the tool \( T2 \).

A critical step is the coding of solutions, which aims to make them more manipulative. The structure of the chromosome (process plan) is illustrated by regrouping machines, configurations, and tools under triplets. A chromosome is encoded as a matrix, where its elements take real values between 0 and 1 (0 and 1 are excluded) as shown in Table 4, where the first and second rows represent, respectively, a code of the operation index and the triplet index.

This coded solution must be decoded column by column, starting with a generation of the operations sequences with respect to the precedence constraints. Then, the sets of triplets are associated with each of the operations in randomly generated sequences. In Algorithm 1, a detailed description of the decoding procedure is presented for decoding the coded process plan of Table 4. The obtained process plan is illustrated in Table 3.

#### Algorithm 1 Process plan decoding.

1: input data \( M = (a_{i,j}) \): matrix of the coded process plan
2: \( p \): process plan
3: for \( i = 1 : n \) do
4: \( \text{get noPred : the list of operations whith no unperformed predecessors} \)
5: \( \text{indexOperation = [size(noPred)]} \)
6: \( p_{operation}^{i} = \text{noPred(indexOperation)} \)
7: \( \text{indexTriplet = noPred(indexOperation)} \)
8: \( p_{triplet}^{i} = T_{p_{operation}^{i}}(indexTriplet) \)
9: for \( j \in successors(p_{operation}^{i}) \) do
10: \( \text{delete } p_{operation}^{i} \text{ from predecessors(j)} \)
11: end for
12: end for
13: return process plan

The obtained set of process plans (coded as in Table 4) is computed by using the objective functions formulated...
in Section 3. Since the optimization of our problem is guided by four objective functions: total production cost, total production time, the amount of hazardous liquid waste, and the amount of greenhouse gases emitted, a Pareto front of the non-dominated solutions/process plans is generated.

### 4.2 Genetic operators

In this study, three genetic operators, namely crossover, mutation, and perturbation, are used.

- **Crossover**: it is the most important operator in genetic algorithms. Randomly, a crossover point is selected, and two chromosomes exchange parts of their chains to create new chromosomes called offsprings or children. Figure 2 illustrates an example of crossover operations.

- **Mutation**: it consists of randomly modifying one or more genes from a given chromosome to create a new offspring or child. In our case, independently of the size of the chromosome, only two columns are randomly selected, as shown in the example of Fig. 3. We can see that column 2 and column 5 are selected and should randomly mutate. Provided that the obtained offspring or child still a feasible process plan, which will be evaluated by using the sets of possible operations sequences and possible triplets.

- **Perturbation**: it consists of randomly selecting a certain percentage of chromosomes from the population that should be mutated. Instead of using mutation, the chromosomes will be perturbed, as shown in Fig. 4. We can see that all the chromosome genes are randomly perturbed to obtain a new offspring or child. Still, the obtained chromosome corresponds to a feasible process plan.

### 4.3 Adapted evolutionary algorithms

This section describes the adapted multi-objective evolutionary approaches, namely, WGA, RWGA, NSGA-II, and NSGA-III to solve our problem.

#### 4.3.1 Weighted genetic algorithm

Weighted genetic algorithm (WGA) is a classical multi-objective evolutionary-based approach, where the decision-maker assigns weights or priorities to the different objectives. Each objective $i$ is associated with a weight $w_i$ such that $0 \leq w_i \leq 1$ and $\sum_{i=1}^{K} w_i = 1$, where $K$ is the number of objectives. In our case, for each objective $w_i = 0.25$ and $\sum_{i=1}^{4} w_i = 1$. At each generation, WGA works as a single objective function during the selection phase by computing the overall fitness of the objectives as depicted in Eq. (15).

$$f(x) = w_1 f_1(x) + w_2 f_2(x) + w_3 f_{LHW}(x) + w_4 f_{GHG}(x)$$

The adapted WGA consists in the following five steps:

**Step 1 (Initialization)**: Generate an initial population $P$.

**Step 2 (Evaluation)**: Evaluate the fitness function of each solution $x \in P_t$ using Eq. (15).

**Step 3 (Selection)**: Select parents based on ranking the fitness function value assigned in step 2.

**Step 4 (Crossover and Mutation)**: Apply crossover on the selected parent pairs to create $N$ offspring. Mutate offspring with a predefined mutation rate. Copy all offspring to $P_{t+1}$.

| Operation | 0.34 | 0.45 | 0.76 | 0.12 | 0.55 | 0.87 | 0.62 |
|-----------|------|------|------|------|------|------|------|
| Triplet   | 0.87 | 0.08 | 0.67 | 0.21 | 0.17 | 0.39 | 0.56 |

Fig. 2 Illustrative crossover operations

Fig. 3 Illustrative mutation operations

3749
Step 5: If the stopping condition is not satisfied, set $t = t + 1$ and go to step 2. Otherwise STOP.

4.3.2 Random weighted genetic algorithm

Random weighted genetic algorithm (RWGA) was proposed by [40]. It is based on a weighted sum of multiple objective functions, where a normalized weight vector randomly generated is used for each solution during the selection phase at each generation. Let us consider:

- $E$ external archive to store non-dominated solutions found during the search so far.
- $n_E$ number of elitist solutions immigrating from $E$ to $P$ in each generation.

More detailed descriptions of the RWGA is presented in [41]. A brief description of the adapted RWGA is summarized in the following six steps:

**Step 1 (Initialization):** Generate an initial population $P$.

**Step 2 (Evaluation):** Evaluate the fitness function of each solution $x \in P_t$ by performing the following steps:

1. **Step 2.1:** Generate a random number $u_k$ in $[0,1]$ for each objective $k$, $k = 1 \ldots K$.
2. **Step 2.2:** Calculate the random weight of each objective $k$ as:
   
   $w_k = \left( \frac{1}{n_E} \right) \sum_{i=1}^{K} u_i$.

3. **Step 2.3:** Calculate the fitness of solution $x$ as:
   
   $f(x) = \sum_{i=1}^{K} w_i \times f_i(x)$

**Step 3 (Selection):** Select parents according to the selection probability $P(x)$ associated with each solution $x \in P_t$ as:

$$P(x) = \frac{f(x) - f_{min}}{\sum_{y \in P_t} (f(y) - f_{min})}$$

Where: $f_{min} = min\{f(x) / x \in P_t\}$

**Step 4 (Crossover and Mutation):** Apply crossover on the selected parent pairs to create $N$ offspring. Mutate offspring with a predefined mutation rate. Copy all offspring to $P_{t+1}$.

**Step 5:** Randomly remove $n_E$ solutions from $P_{t+1}$ and add the same number of solutions from $E$ to $P_{t+1}$.

**Step 6:** If the stopping condition is not satisfied, set $t = t + 1$ and go to step 2. Otherwise, return to $E$.

4.3.3 Non-dominated sorting genetic algorithm II

Non-dominated sorting genetic algorithm II (NSGA-II) is a revised version of the Non-dominated Sorting Genetic Algorithm (NSGA) [42]. The NSGA-II mechanism begins by ranking the solutions according to their non-domination score to get a set of Pareto front solutions. Then, using the crowding distance technique to maintain the diversity of solutions on the Pareto front, applied on the last front to complete the next-generation parent population size.

Algorithm 2 presents the main steps of NSGA-II. Furthermore, for clear descriptions of the used coded process plan as well as the mutation and the crossover operators, refer to [8].

### Algorithm 2 NSGA-II algorithm.

1: input data
2: initialize Population Size, Number of iterations, Crossover, Mutation, Perturbation Ratio
3: randomize parent Population
4: for iter = 1 : Number of iterations do
5:     generate child Population from parent Population
6:     population = parent Population $\cup$ child Population
7:     $F$ = fastNonDominatedSorting(population)
8:     for $I = 1 : size(F)$ do
9:         if size(new Population) + size($F_i$) < Population Size then
10:             new Population$+$ = $F_i$
11:         else
12:             crowdingDistanceSorting($F_i$)
13:             for $k = 1 : size(F_i)$ do
14:                 if size(new Population) < Population Size then
15:                     new Population$+$ = $F_i^k$
16:                 else
17:                     break;
18:             end if
19:         end for
20:     end if
21: end for
22: parent Population = new Population
23: end for
24: return parent Population

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4.3.4 Non-dominated sorting genetic algorithm III

Non-dominated sorting genetic algorithm III (NSGA-III) is an extension of NSGA-II, developed by [43]. It is designed to improve the ability to solve the multi-objective optimization problem by changing the selection mechanism. Instead of the traditional crowding operator used in NSGA-II, NSGA-III adopts a reference point based niche mechanism to guide the population to approach the diversity of the Pareto fronts. To achieve this, objective values and reference points are first normalized to have an identical range.

Note that the same procedures used for NSGA-II are being considered for initial population, crossover, and mutation operators for NSGA-III.

Algorithm 3 NSGA-III algorithm.

1: Calculate the number of reference points \( H \) to place on the hyper-plan
2: Generate the initial population at random, taking into account the resources assignment constraints (POP chromosomes)
3: Realize the non-dominated population sorting
4: for \( i = 1 \) Stopping criteria do
5: Select two parents \( P1 \) and \( P2 \) using the tournament method
6: Apply the crossover between \( P1 \) and \( P2 \) with a probability \( P_c \)
7: Compute the non-dominated population sorting
8: Normalize the population members
9: Associate the population member with the reference points
10: Apply the niche preservation (counter)
11: Keep the niche obtained solutions for the next generation
12: end for

4.4 TOPSIS

Technique for order preference by similarity to ideal solution (TOPSIS) is one of the well-known multi-criteria decision making techniques used for ranking and selection among a set of alternatives via the Euclidean distance, developed by [44]. It is defined by seven steps, as follows:

Step 1: Construct the decision matrix \( X \) and the criteria weights \( W \) Let \( X = (x_{ij})_{\alpha \times \beta} \) is the decision matrix and \( W = [w_1, w_2, \ldots, w_\beta] \) weights vector given by the decision marker to present their preferences between criteria, with \( \sum_{j=1}^{\beta} w_j = 1 \).

Step 2: Compute the normalized decision matrix for \( i = 1, \ldots, \alpha ; j = 1, \ldots, \beta \)

\[
 r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{\alpha} x_{ij}^2}}
\]

Step 3: Compute the weighted normalized decision matrix \( V = (v_{ij}) \)

\[
 v_{ij} = w_j \times x_{ij}
\]

where : \( w_j \) is the weight of the \( j^{th} \) criterion.

Step 4: Determine the positive ideal \( A^+ \) and negative ideal \( A^- \)

\[
 A^+ = (v_{11}^+, v_{21}^+, \ldots, v_{\beta 1}^+ = (Best(v_{1j}), Best(v_{2j}), \ldots, Best(v_{\alpha j}))
\]

\[
 A^- = (v_{11}^-, v_{21}^-, \ldots, v_{\beta 1}^- = (Worst(v_{1j}), Worst(v_{2j}), \ldots, Worst(v_{\alpha j}))
\]

Where :

\[
 Best_j(v_{ij}) = \begin{cases} 
 \max(v_{ij}) & \text{if criteria j is benefical} \\
 \min(v_{ij}) & \text{if criteria j is not benefical}
\end{cases}
\]

\[
 Worst_j(v_{ij}) = \begin{cases} 
 \min(v_{ij}) & \text{if criteria j is benefical} \\
 \max(v_{ij}) & \text{if criteria j is not benefical}
\end{cases}
\]

Step 5: For each alternative, compute the Euclidean distances from the positive ideal \( A^+ \) and negative ideal \( A^- \)

\[
 d_i^+ = \sqrt{\sum_{j=1}^{\beta} (v_{ij} - v_{ij}^+)^2}, i = 1 \ldots \alpha
\]

\[
 d_i^- = \sqrt{\sum_{j=1}^{\beta} (v_{ij} - v_{ij}^-)^2}, i = 1 \ldots \alpha
\]

Step 6: Calculate the relative closeness of each alternative to the ideal solution

\[
 C_i^+ = \frac{d_i^-}{d_i^- + d_i^+}
\]

Where: \( 0 \leq C_i^+ \leq 1 \)

Step 7: Rank the alternatives according to the relative closeness
The more \( C_i^+ \) is important, the more desirable the alternative \( i \) is.

4.5 Comparison metrics

In this section, to analyze the obtained Pareto fronts and to compare the performances of the adapted evolutionary
approaches, two well-known metrics, respectively hypervolume and spacing metric, are used.

4.5.1 Hypervolume metric

The hypervolume (HV) metric (or s-metric) has been used by many authors [45], which is a performance metric for indicating the quality of non-dominated solutions sets ND. It reflects the diversity and the uniformity of the non-dominated solutions. This metric calculates the volume (in the objective space) covered by solutions that belong to a non-dominated sets obtained by the proposed approaches and delimited from above by a reference point \( r \), which is the anti-optimal point defined as the worst solution inside the objective space.

The mathematical expression of HV metric is calculated by Eq. (16):

\[
HV(ND, r) = \bigwedge (\bigcup h(S_t)) | S_t \in ND, t = 1, \ldots, \theta)
\]

(16)

Where:

- \( \theta \): is the number of solutions that are included in the Pareto front.
- \( \mu \): is the number of objective functions
- \( S_t \): the solution of a non-dominated solutions set and \( t = [1, \ldots, \theta] \)
- \( h(S_t) = |S_{t1} - r_1| \times |S_{t2} - r_2| \times |S_{t3} - r_3| \times \cdots \times |S_{t\mu} - r_\mu| \wedge (.) \): denotes the Lebesgue measure

The larger the HV value is, the better the algorithm is.

4.5.2 Spacing metric

The spacing metric (SM) is used usually to demonstrate the uniformity of attained Pareto frontier (how evenly the non-dominated process plan are distributed along the Pareto front). Equation (17) calculates the spacing metric:

\[
Spacing = \sqrt{\frac{1}{\Omega} - \frac{1}{\Omega} \sum_{i=1}^{\Omega} (d_i - \bar{d})^2}
\]

(17)

where:

- \( f_1, f_2, f_3, \) and \( f_4 \): respectively represent, the sustainability-metric, time, and cost objective functions.
- \( \Omega \): represents the number of non-dominated solutions in each frontier.
- \( d_i \): represents the minimum distance between two solutions in the attained front Pareto and \( \bar{d} \) is mean of the obtained \( d_i \).
- \( d_i = \min(|f_{i1} - f_{j1}| + |f_{i2} - f_{j2}| + |f_{i3} - f_{j3}| + |f_{i4} - f_{j4}|) \), \( i, j = 1, 2, \ldots, \Omega, i \neq j \)
- \( \bar{d} = \frac{1}{\Omega} \sum_{i=1}^{\Omega} d_i \)

The less the spacing is, the more desirable is the value.

### Table 5 National and European emission factors for consumed electricity (Koffi et al. [46])

| Country       | Standard emission factor \((TCO_2 / MWH)\) | LCA emission factor \((TCO_2 - EQ / MWH)\) | Country       | Standard emission factor \((TCO_2 / MWH)\) | LCA emission factor \((TCO_2 - EQ / MWH)\) |
|---------------|---------------------------------------------|---------------------------------------------|---------------|---------------------------------------------|---------------------------------------------|
| Austria       | 0.209                                       | 0.310                                       | Sweden        | 0.023                                       | 0.079                                       |
| Belgium       | 0.285                                       | 0.402                                       | Bulgaria      | 0.819                                       | 0.906                                       |
| Germany       | 0.624                                       | 0.706                                       | Cyprus        | 0.874                                       | 1.019                                       |
| Denmark       | 0.461                                       | 0.760                                       | Czech Republic| 0.950                                       | 0.802                                       |
| Spain         | 0.440                                       | 0.639                                       | Estonia       | 0.908                                       | 1.593                                       |
| Finland       | 0.216                                       | 0.418                                       | Hungary       | 0.566                                       | 0.678                                       |
| France        | 0.056                                       | 0.146                                       | Lithuania     | 0.153                                       | 0.174                                       |
| United Kingdom| 0.543                                       | 0.658                                       | Latvia        | 0.109                                       | 0.563                                       |
| Greece        | 1.149                                       | 1.167                                       | Poland        | 1.191                                       | 1.185                                       |
| Ireland       | 0.732                                       | 0.870                                       | Romania       | 0.701                                       | 1.084                                       |
| Italy         | 0.483                                       | 0.708                                       | Slovenia      | 0.557                                       | 0.602                                       |
| Netherlands   | 0.435                                       | 0.716                                       | Slovakia      | 0.252                                       | 0.353                                       |
| Portugal      | 0.369                                       | 0.750                                       | EU-27         | 0.460                                       | 0.578                                       |

**Note:** The standard emission factors following the Intergovernmental Panel on Climate Change (IPCC) principles are based on the carbon contents in the fuels. For simplicity, the emission factors presented here assume that all carbon in the fuel forms \( CO_2 \). Life Cycle Assessment (LCA) emission factors take into account the overall life cycle of the energy carrier. This way of computation includes not only the emissions of the final combustion, but also all emissions of the supply chain.
Table 6: Global warming potentials of Kyoto protocol greenhouse gases (Eurostat, 2010)

| Chemical formula | Greenhouse gas            | Global warming potential $(GWP)_{(1)}$ |
|------------------|---------------------------|----------------------------------------|
| $CO_2$           | Carbon dioxide            | 1                                      |
| $CH_4$           | Methane                   | 21                                     |
| $N_2O$           | Nitrous oxide             | 310                                    |
| $HFCs$           | Hydrofluorocarbons        | 140 $(C_2H_4F_2)$ to 11700 $(CHF_3)$   |
| $PFCs$           | Perfluorocarbons          | 5700 $(CF_4)$ to 11900 $(C_2F_6)$      |
| $SF_6$           | Sulfur hexafluoride       | 23900                                  |

Note: (1): In a 100-year time horizon. Reading guide: For example, one ton of methane equates to 21 tons of $CO_2$

4.6 Used GHG parameters

The emitted gases include the emissions from energy consumption and the type of operations. The emission factor for electricity consumption ($f_{e,f}$) is based on the covenant of mayors agreement [46]. Table 5 represents the national and European emission factors for consumed electricity. Where Table 6 represents the GWP of Kyoto protocol greenhouse gases (Eurostat, 2010), GWP factor represents global warming potential and is used to convert emissions of other greenhouse gases into $CO_2$ equivalents.

5 Experimental results and analyses

This section describes our experiments’ results realized using an Intel Core i3 1.7 GHz processor and 4 GB RAM. The four approaches are implemented with a Java-Cplex. An instance is defined by the number of operations and the number of available reconfigurable machines and represented by \( nbOperations-nbMachines \).

Initially, to evaluate the influence of genetic operators’ probabilities on the convergence of the algorithms, we study different scenarios and compare the cardinalities of the obtained Pareto fronts. We show in the following the obtained results of NSGA-III, where a scenario is defined by the probability of its mutation operator (i.e., NSGA-III-10 is an adapted NSGA-III scenario where 10% of the child’s population is generated by mutation operations, while the rest 90% is the result of crossover operations). Five scenarios are considered, NSGA-III-0, NSGA-III-10, NSGA-III-50, NSGA-III-90, and NSGA-III-100, respectively. In each scenario, the results are compared and analyzed. Table 7 presents the cardinality of the Pareto front (i.e., number of obtained Pareto optimal process plans) of each scenario in the case of 100 operations and 20 reconfigurable machines, where the population size is 40 individuals and the number of iterations attempts 2000.

Table 8 presents a comparison of the Pareto fronts obtained for the five scenarios when all the fronts are mixed in one new Pareto front. We can see that the adapted NSGA-III-90 completely dominates NSGA-III-0, NSGA-III-10, NSGA-III-50, and NSGA-III-100, which confirm that NSGA-III-90 is the best scenario.

Based on the sensitivity analysis of the parameters of NSGA-III, we use the parameters that showed the best performance overall. Table 9 shows the different parameters used by WGA, RWGA, NSGA-II, and NSGA-III. Hence, the number of iterations of the algorithm is equal to 1000, and for each iteration, we have 40 chromosomes (individuals), 10% of the population (i.e., 4 chromosomes) will use the crossover operator, and 90% of the population (i.e., 36 chromosomes) will use the mutation and perturbation operators. The perturbation ratio indicates the percentage of the chromosomes (30%, in our case) which will be perturbed. Hence, 11 chromosomes from the 36 chromosomes will be perturbed.

Table 10 presents the experimental results obtained using each approach (WGA, RWGA, NSGA-II, and NSGA-III), where two performance indicators are used, the CPU calculation time (in seconds) and the cardinality of the Pareto fronts (number of optimal Pareto process plans) of each instance.

Table 7: The probabilities of genetic operators and cardinality of the Pareto fronts on the convergence of NSGA-III

| Scenario | 1 | 2 | 3 | 4 | 5 |
|----------|---|---|---|---|---|
| Scenario | NSGA-III-0 | NSGA-III-10 | NSGA-III-50 | NSGA-III-90 | NSGA-III-100 |
| Pmutation | 0 | 10 | 50 | 90 | 100 |
| Pcrossover | 100 | 90 | 50 | 10 | 0 |
| Cardinality of the Pareto fronts | 16 | 22 | 5 | 37 | 12 |
### Table 8  Comparisons of the performances of NSGA-III

| Scenario | NSGA-III-0 | NSGA-III-10 | NSGA-III-50 | NSGA-III-90 | NSGA-III-100 |
|----------|------------|--------------|-------------|-------------|--------------|
| 1        | 37         | 0            | 0           | 0           | 37           |
| 2        | 0          | 0            | 0           | 0           | 0            |
| 3        | 0          | 0            | 0           | 0           | 0            |
| 4        | 0          | 0            | 0           | 0           | 0            |
| 5        | 0          | 0            | 0           | 0           | 0            |

Cardinality of the Pareto fronts

### Table 9  The based parameters settings

| Population size | Number of iterations | Pcrossover | Pmutation | Perturbation ratio |
|-----------------|----------------------|------------|-----------|--------------------|
| 40              | 1000                 | 0.1        | 0.9       | 0.3                |

### Table 10  CPU time and cardinality of the Pareto fronts of NSGA-II, NSGA-III, WGA, and RWGA

| Instance | CPU (seconds) | NSGA-II | NSGA-III | WGA | RWGA | NSGA-II | NSGA-III | WGA | RWGA |
|----------|---------------|---------|----------|-----|------|---------|----------|-----|------|
| 11-6     | 909.56        | 586.39  | 1098.13  | 4684.85 | 23 | 13 | 8 | 9 |
| 12-6     | 1031.09       | 656.34  | 1136.08  | 4696.99 | 12 | 11 | 5 | 3 |
| 14-5     | 1072.30       | 687.96  | 1194.46  | 4690.97 | 7  | 6  | 5 | 8 |
| 20-10    | 1525.80       | 1104.39 | 1580.56  | 4735.45 | 14 | 8  | 4 | 2 |
| 30-15    | 2212.30       | 1682.36 | 2094.64  | 4883.73 | 36 | 27 | 4 | 4 |
| 45-20    | 3590.60       | 2948.70 | 3287.12  | 4907.54 | 5  | 6  | 8 | 2 |
| 50-20    | 3764.54       | 3544.74 | 3454.49  | 4931.50 | 7  | 13 | 4 | 3 |
| x100-20  | 8371.45       | 8198.70 | 7195.37  | 5326.42 | 11 | 13 | 8 | 2 |
| 00-20bis | 33022.97      | 31921.36 | 26740.72 | 21794.44 | 21 | 37 | 5 | 2 |

Bold entries indicate best values

### Table 11  Comparisons of the performances of NSGA-III, WGA, and RWGA

| Instance | Combined Pareto fronts of NSGA-III, WGA, and RWGA |
|----------|---------------------------------------------------|
|          | Total cardinality | # Pareto front of NSGA-III | # Pareto front of WGA | # Pareto front of RWGA |
| 11-6     | 15 | 12 | 2 | 1 |
| 12-6     | 11 | 11 | 0 | 0 |
| 14-5     | 6  | 6  | 0 | 0 |
| 20-10    | 8  | 8  | 0 | 0 |
| 30-15    | 27 | 27 | 0 | 0 |
| 45-20    | 6  | 6  | 0 | 0 |
| 50-20    | 13 | 13 | 0 | 0 |
| 100-20   | 13 | 13 | 0 | 0 |
| 100-20bis| 37 | 37 | 0 | 0 |
Table 12  Hypervolume of NSGA-II, NSGA-III, WGA, and RWGA

| Instance | Hypervolume  |
|----------|-------------|
|          | NSGA-II     | NSGA-III   | WGA         | RWGA        |
| 11-6     | 7.12e+102   | 1.20e+58   | 7.91e+35    | 3.39e+40    |
| 12-6     | 2.62e+53    | 9.45e+48   | 3.42e+22    | 3.12e+13    |
| 14-5     | 6.38e+31    | 1.8557e+27 | 1.15e+23    | 4.9316e+26  |
| 20-10    | 6.43e+65    | 4.04e+37   | 1.33e+19    | 3.64e+9     |
| 30-15    | 1.14e+173   | 5.32e+129  | 4.73e+19    | 4.28e+19    |
| 45-20    | 1.04e+25    | 6.44e+30   | 3.89e+29    | 1.40e+10    |
| 50-20    | 5.94e+35    | 1.95e+66   | 3.72e+20    | 2.66e+15    |
| 100-20   | 6.87e+59    | 5.06e+70   | 7.40e+43    | 8.4799e+10  |
| 100-20bis| 6.69e+113   | 2.31e+200  | 2.26e+27    | 8.634e+10   |

Bold entries indicate best values

Table 13  Spacing metric of NSGA-II, NSGA-III, WGA, and RWGA

| Instance | Spacing metric  |
|----------|----------------|
|          | NSGA-II        | NSGA-III   | WGA         | RWGA        |
| 11-6     | 215.87         | 220.45     | 879.81      | 304.90      |
| 12-6     | 143.71         | 138.54     | 809.25      | 1863.37     |
| 14-5     | 1050.6         | 118.77     | 323.64      | 432.68      |
| 20-10    | 575.83         | 390.55     | 1130.3      | -           |
| 30-15    | 388.65         | 296.47     | 753.29      | 277.70      |
| 45-20    | 1420           | 417.36     | 2412.7      | -           |
| 50-20    | 1150           | 321.57     | 2129.98     | 2771.9      |
| 100-20   | 5630           | 5941.8     | 6775.1      | -           |
| 100-20bis| 188.5          | 185.24     | 688.79      | -           |

Bold entries indicate best values

Table 14  Pareto optimal process plans ranking using TOPSIS

| Process plan | Rank | Pareto optimal fronts ranking using TOPSIS |
|--------------|------|------------------------------------------|
|              |      | \( f_1 (E) \)      | \( f_1 \) (min) | \( f_{LHW} \) (H.u) | \( f_{GHG} \) (g) |
| PP_{13}      | 1    | 21494 | 1782     | 269943 | 20738 |
| PP_{4}       | 2    | 21677 | 1777     | 270346 | 20722 |
| PP_{8}       | 3    | 22087 | 1736     | 273860 | 20440 |
| PP_{11}      | 4    | 21889 | 1762     | 272162 | 20725 |
| PP_{9}       | 5    | 21881 | 1732     | 275843 | 20675 |
| PP_{5}       | 6    | 21129 | 1733     | 276054 | 20913 |
| PP_{6}       | 7    | 21617 | 1781     | 274429 | 20969 |
| PP_{7}       | 8    | 21768 | 1762     | 276762 | 20862 |
| PP_{3}       | 9    | 21601 | 1773     | 275484 | 21013 |
| PP_{2}       | 10   | 21400 | 1810     | 273813 | 21092 |
| PP_{10}      | 11   | 21490 | 1796     | 275723 | 20987 |
| PP_{12}      | 12   | 21010 | 1710     | 279729 | 20861 |
| PP_{1}       | 13   | 22031 | 1709     | 300441 | 21489 |

Bold entries indicate best values
Table 11 presents a comparison of the Pareto fronts obtained by NSGA-III, WGA, and RWGA, when the three fronts are mixed in one new Pareto front, where:

- **Total cardinality**: it corresponds to the size of the new Pareto front (i.e., number of Pareto optimal process plans).
- **# Pareto front of WGA**: it presents the number of Pareto optimal process plans obtained from WGA which are maintained in the new Pareto front (i.e., contribution of WGA Pareto front in the new mixed Pareto front).
- **# Pareto front of RWGA**: it presents the number of Pareto optimal process plans obtained from WGA which are maintained in the new Pareto front (i.e., contribution of RWGA Pareto front in the new mixed Pareto front).
- **# Pareto front of NSGA-III**: it presents the number of Pareto optimal process plans obtained from NSGA-III which are maintained in the new Pareto front (i.e., contribution of NSGA-III Pareto front in the new mixed Pareto front).

Table 12 and Table 13 show the hypervolume metric and spacing metric values associated with the obtained Pareto fronts for different instances using respectively NSGA-II, NSGA-III, WGA, and RWGA.

**Note**: For instances 20-10, 45-20, 100-20, and 100-20bis, when using RWGA, we have two optimal process plans where the spacing metric value automatically equals zero since the computed distance is equal to zero.

Four main observations can be taken from the above numerical results:

- **Observations 1**: From Table 10, RWGA has a time inconvenient in solving the problem. For the largest instance, WGA has shown better time consuming, but NSGA-III has acquired more Pareto fronts. On the other side, for smaller instances, NSGA-III takes less time, including that the most powerful is NSGA-II for the cardinality.
- **Observations 2**: From Table 11, we observe that NSGA-III dominates the other approaches completely.
- **Observations 3**: While the number of iterations increases (the last lines of Table 11 and Table 10, instance 100-20bis), NSGA-III outperforms NSGA-II, WGA, and RWGA. It shows that NSGA-III enriches the Pareto fronts and gives decision-makers more variety of process plans to select.
- **Observations 4**: From Table 12 and Table 13, the results confirm that NSGA-III performs better and indicates a significant progression of the region covered by the solutions of the Pareto front.

Making a specific decision based on the results obtained without using TOPSIS technique is very difficult while ensuring the best compromise between four objectives: total production cost, total production time, amount of hazardous liquid waste and amount of greenhouse gases emitted. Before applying TOPSIS, it is important to define the objectives’ weights so that TOPSIS can rank the different Pareto optimal process plans. In our case, the weights are respectively 0.15, 0.15, 0.35, and 0.35. Table 14 illustrates...
the ranking of the Pareto optimal process plans obtained using NSGA-III in case the of 100 operations and 20 reconfigurable machines when the number of iterations attempts 1000. We have a total of 13 Pareto optimal process plans as shown in Fig. 5.

- Observation 5: From Table 14, based on the weights associated with the four objectives, we can see that, TOPSIS ranks: (i) \( PP_{13} \) first with a total production cost equals to 21494 (€), a total production time equals 1782 (minutes), a total amount of hazardous waste equals 269943 (Hazardous unit) and a total amount of emitted greenhouse gases equals to 20738 (g) and (ii) \( PP_{1} \) last with a total production cost equals to 22031 (€), a total production time equals 1709 (minutes), a total amount of hazardous waste equals 300441 (Hazardous unit) and a total amount of emitted greenhouse gases equals to 21489 (g). We can see that hazardous waste and emitted greenhouse gases are predominant in ranking the Pareto optimal process plans.

6 Conclusions

In this paper, we considered an environmental-oriented multi-objective reconfigurable manufacturing system design (i.e., sustainable reconfigurable machines and tools selection) in the case of a single-unit process plan generation. A non-linear multi-objective integer program (NL-MOIP) was presented, where four objectives are minimized. Nevertheless, even if the total production cost and the total production time were modeled easily, the amount of greenhouse gases and the hazardous liquid wastes emitted by the machines were complex to formulate. Second, we adapted four evolutionary approaches to tackle the problem, respectively, WGA, RWGA, NSGA-II, and NSGA-III. To compare the efficiency of the four approaches, several instances of the problem were experimented and the obtained results analyzed using three metrics, respectively hypervolume, spacing metric, and cardinality of the mixed Pareto fronts. Furthermore, the influences of the probabilities of genetic operators on the convergence of the adapted NSGA-III were evaluated, and the TOPSIS method was used to help the decision-maker ranking and select the best process plans.

The process plan generation belongs to the domain of NP-hard combinatorial problems, especially in reconfigurable environments. For real-life applications, since the complexity increases, as the inputs increase with the objectives to optimize, it is generally complex to implement the proposed non-linear multi-objective integer program. Hence, with the help of rich experimental results and analyses, the advantages and disadvantages of the adapted evolutionary-based approaches were highlighted using several metrics. Moreover, if the decision-maker prefers the computational time, WGA and RWGA are appropriate. Nevertheless, if he prefers the quality of the solutions (optimal Pareto process plans), NSGA-II and NSGA-III can be used, but more computational time will be necessary.

For future works, in addition to reducing the traditional total production cost and completion time, minimizing the maximum machines exploitation time can be considered as a novel optimization criterion for high-quality products. Other evolutionary-based approaches such as AMOSA and MOPSO can be adapted and compared. Moreover, we intend to extend the work to address the multi-unit process plan generation problem. Finally, the integration of process plan generation and scheduling problems in a sustainable reconfigurable manufacturing environment (S-IPPS: sustainable integrated process planning and scheduling) for multiple contexts, such as dynamic, stochastic, and smart, will be challenging and of great interests.

Author contribution All the authors have involved equally in the realized work.

1. Miss Khettabi: paper writing, problem formulation, approaches proposal and experimental performing and analysis
2. Prof. Benyoucef: paper writing, problem formulation, approaches proposal and experimental performing and analysis
3. Prof. Boutiche: paper writing, problem formulation, approaches proposal and experimental performing and analysis.

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Declarations

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