



HAL
open science

Sustainable Process Plan Generation in RMS: A Comparative Study of Two Multi-objective Evolutionary Approaches

Imen Khettabi, Lyes Benyoucef, Mohamed Amine Boutiche

► **To cite this version:**

Imen Khettabi, Lyes Benyoucef, Mohamed Amine Boutiche. Sustainable Process Plan Generation in RMS: A Comparative Study of Two Multi-objective Evolutionary Approaches. IFIP International Conference on Advances in Production Management Systems (APMS), Sep 2021, Nantes, France. pp.329-339, 10.1007/978-3-030-85906-0_37. hal-03526660

HAL Id: hal-03526660

<https://hal.science/hal-03526660>

Submitted on 14 Jan 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License



This document is the original author manuscript of a paper submitted to an IFIP conference proceedings or other IFIP publication by Springer Nature. As such, there may be some differences in the official published version of the paper. Such differences, if any, are usually due to reformatting during preparation for publication or minor corrections made by the author(s) during final proofreading of the publication manuscript.

Sustainable Process Plan Generation in RMS: A Comparative Study of Two Multi-objective Evolutionary Approaches

Imen Khettabi¹, Lyes Benyoucef², and Mohamed Amine Boutiche¹

¹ DGRSDT, LaROMaD Laboratory, USTHB University, Algiers, Algeria
`imen.khettabi1@gmail.com`, `mboutiche@usthb.dz`

² Aix Marseille University, University of Touloun, CNRS, LIS, Marseille, France
`lyes.benyoucef@lis-lab.fr`

Abstract. In today's manufacturing industry, staying competitive requires being both cost and time effective, as well as being environmentally benign. In this paper, two versions of the well-known non-dominated sorting genetic algorithm (NSGA) namely Dynamic-NSGA-II and NSGA-III are proposed and compared to solve an environmental oriented multi-objective single unit process plan generation problem in a reconfigurable manufacturing environment. In addition to the traditional total production cost and total production time, two other criteria namely, total amount of hazardous liquid waste and total amount of greenhouse gases (GHG) emitted are minimized. Firstly, a non-linear multi-objective integer program (NL-MOIP) is proposed. Secondly, to illustrate the efficiency of the two approaches, several instances of the problem are experimented and the obtained results are analyzed using three metrics respectively spacing metric, inverted generational distance and cardinality of the mixed Pareto fronts.

Keywords: Sustainability · RMS · Process plan generation · Multi-objective optimization · Dynamic-NSGA-II · NSGA-III.

1 Introduction

Reconfigurable manufacturing system (RMS) is one of the latest manufacturing paradigms. In this paradigm, machine components, machines softwares or material handling units can be added, removed, modified or interchanged as needed and when imposed by the necessity to react and respond rapidly and cost-effectively to changing requirements. RMS is regarded as a convenient manufacturing paradigm for variety productions as well as a flexible enabler for this variety. Hence, it is a logical evolution of the two manufacturing systems already used in the industries respectively dedicated manufacturing lines (DML) and flexible manufacturing systems (FMS). According to Koren [1], father of RMS, DMLs are inexpensive but their capacities are not fully utilized in several situations especially under the pressure of global competition, thus they engender losses. On the other hand, FMSs respond to product changes, but they are not

designed for structural changes. Hence, in both systems, a sudden market variation cannot be countered, like demand fluctuation or regulatory requirements. RMS combines the high flexibility of FMS with the high production rate of DML. It comprises the positive features of both systems, thanks to its adjustable structure and design focus.

Nowadays, RMS is a very active research field where multiple state of the arts have been dedicated covering many areas, such as design, layout optimization, reconfigurable control, process planning and production scheduling, etc. In a multi-objective context, [2] used an adapted version of NSGA-II to integrate process plan generation to the design problem. In [3], the authors introduced the concept of reconfigurable and energy efficient manufacturing system (REMS) and proposed a discrete event simulation model to evaluate its energy efficiency. Moreover, [4] presented a quantitative framework for sustainable manufacturing explaining how it can be applied to the automotive industry and how material alternatives can help to achieve sustainability objectives. Toward sustainable RMSs and system design through process plan generation, the authors in [5] proposed a comparative study of an iterative multi-objective integer linear programming (I-MOILP) approach with adapted versions of AMOSA and NSGA-II algorithms. Recently, [6] showed how the RMSs concepts can lead to the design of sustainable and energy efficient manufacturing systems and how to decrease the emissions and energy consumption during the life cycle.

In this paper, we adapt two evolutionary approaches, respectively Dynamic-NSGA-II and NSGA-III, to solve an environmental oriented multi-objective single unit process plan generation problem in a reconfigurable environment. Some experimental results are presented and analyzed using three metrics namely spacing metric, inverted generational distance and cardinality of the mixed Pareto fronts. The rest of the paper is organized as follows. Section 2 presents the problem under consideration and its mathematical formulation. Section 3 describes the proposed two approaches. Section 4 discusses the experimental results and analyzes. Section 5 concludes the paper with some future work directions.

2 Problem Description and Mathematical Formulation

2.1 Problem Description

Let us consider a single unit of a product to be manufactured in a reconfigurable environment. The product is composed of a set of operations linked by precedence constraints (see Fig. 1). Moreover, three key data define an operation: the precedence constraints, the set of candidate tools and the tool approach directions (TADs) (i.e. $x_{\pm}, y_{\pm}, z_{\pm}$). Once the operations requirements are identified, a machine is able to 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 . The generation of process plan consists of sequencing the operations to be performed on the used machines under the configurations and tools, through the precedence graph as well as the triplets to perform each

operation in the sequence. Table 1 presents a simple example of a generated process plan in our case.

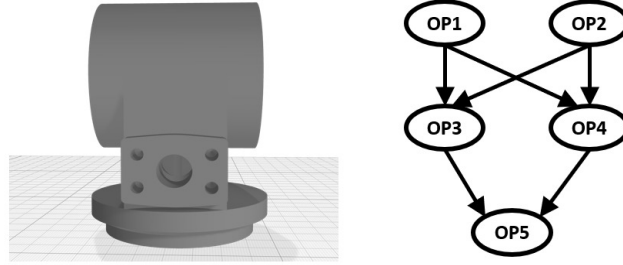


Fig. 1. An illustrative product schema and operations precedence graph

Table 1. Illustrative structure of a process plan

Operation	OP_1	OP_2	OP_3	OP_4	OP_5
Machine	M_2	M_1	M_3	M_3	M_1
Configuration	C_2	C_3	C_1	C_1	C_2
Tool	T_2	T_1	T_3	T_1	T_1

2.2 Mathematical Formulation

The following notations are used:

Parameters

n	Number of operations
OP	Set of operations
i, i'	Index of operations
PR_i	Set of predecessors of operation OP_i
m	Number of machines
M	Set of machines
j, j'	Index of machine
G	Set of greenhouse gases
g	Index of greenhouse gases
$l_{i,t}$	Required liquid for operation OP_i when using triplet t per time unit
$EP_{i,t}$	Estimated hazardous liquid waste for operation OP_i when using triplet t
f_{ef}	Emission factor for electricity consumption
$f_{i,g}$	Operation OP_i emitting greenhouse gas type g per time unit
t, t'	Index of triplet

TO_i	Set of available triplets for operation OP_i
TM_j	Set of available triplets using machine M_j
T	Set of triplets, where $T = TO_i \cup TM_j$
c, c'	Index of configurations
tl, tl'	Index of tools
p, p'	Index of positions in the sequence
GWP_g	Global warning potential for emitted greenhouse gas type g

Cost Parameters

$CCM_{j,j'}$	Machine changeover cost per time unit
$CCC_{c,c'}$	Configuration changeover cost per time unit
$CCT_{tl,tl'}$	Tool changeover cost per time unit
$Pc_{i,t}$	Operation OP_i processing cost when using triplet t per time unit
DC_{GHG}	Disposal cost of the emitted greenhouse gases
DC_{LHW}	Disposal cost of the hazardous liquid waste

Time Parameters

$TCM_{j,j'}$	Machine changeover time
$TCC_{c,c'}$	Configuration changeover time
$TCT_{tl,tl'}$	Tool changeover time
$Pt_{i,t}$	Operation OP_i processing time when using triplet t

Energy Parameters

$ECM_{j,j'}$	Machine changeover energy per time unit
$ECC_{c,c'}$	Configuration changeover energy per time unit
$ECT_{tl,tl'}$	Tool changeover energy
$Pe_{i,t}$	Operation OP_i processing energy when using triplet t per time unit
IEC_j	Initial energy consumption of machine M_j

Decision Variables

- $x_{i,p}^t = 1$ if operation OP_i is using triplet t at the p^{th} position, 0 otherwise.
- $y_{p,t}^m = 1$ if machine M_j is using triplet t at the p^{th} position, 0 otherwise.
- $MCP_p^{p-1}(j, j') = 1$ if there has been a change from machine M_j to machine $M_{j'}$ between positions $p - 1$ and p , 0 otherwise.
- $TCP_p^{j,p-1}(t, t') = 1$ if there has been a change from triplet t to triplet t' of machine M_j between positions $p - 1$ and p , 0 otherwise.

Objective Functions

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

1. The total production cost f_c : Equation (1) shows 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 disposal cost of the emitted hazardous waste during the production.

$$\begin{aligned}
f_c = & \sum_{p=1}^n \sum_{i=1}^n \sum_{t \in TO_i} x_{i,p}^t \times Pc_{i,t} \times Pt_{i,t} + \\
& \sum_{p=2}^n \sum_{j=1}^m \sum_{j'=1}^m MC_p^{p-1}(j, j') \times CCM_{j,j'} \times TCM_{j,j'} + \\
& \sum_{p=2}^n \sum_{j=1}^m \sum_{t \in M_j} \sum_{t' \in M_j} TC_p^{j,p-1}(t, t') \times (CCT_{tl,t'} \times TCT_{tl,t'} + \\
& CCC_{c,c'} \times TCC_{c,c'}) + (DC_{GHG} \times f_{GHG} + DC_{LWH} \times f_{LHW})
\end{aligned} \tag{1}$$

2. The total production time f_t : Equation (2) defines the total production time to be minimized. It includes: machine changeover time, configuration changeover time, tool changeover time and processing time.

$$\begin{aligned}
f_t = & \sum_{p=1}^n \sum_{i=1}^n \sum_{t \in TO_i} x_{i,p}^t \times Pt_{i,t} + \\
& \sum_{p=2}^n \sum_{j=1}^m \sum_{j'=1}^m MC_p^{p-1}(j, j') \times TCM_{j,j'} + \\
& \sum_{p=2}^n \sum_{j=1}^m \sum_{t \in M_j} \sum_{t' \in M_j} TC_p^{j,p-1}(t, t') \times (TCC_{c,c'} + TCT_{tl,t'})
\end{aligned} \tag{2}$$

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

$$f_{LHW} = \sum_{p=1}^n \sum_{i=1}^n \sum_{t \in TO_i} x_{i,p}^t \times l_{i,t} \times Pt_{i,t} \times EP_{i,t} \tag{3}$$

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 warning potential (GWP). In this research work, GWP factor is used to convert emissions of the other greenhouse gases into CO_2 equivalents.

$$f_{GHG} = f_{ef} \times f_{EC} + \sum_{p=1}^n \sum_{i=1}^n \sum_{t \in TO_i} \sum_{g \in G} x_{i,p}^t \times Pt_{i,t} \times f_{i,g} \times GWP_g \tag{4}$$

Equation (5) describes how to compute the total energy consumption f_{EC} during the production process.

$$\begin{aligned}
f_{EC} = & \sum_{p=1}^n \sum_{i=1}^n \sum_{j=1}^m \sum_{t \in TO_i} y_{p,t}^j \times x_{i,p}^t \times IEC_j + \\
& \sum_{p=1}^n \sum_{i=1}^n \sum_{t \in TO_i} x_{i,p}^t \times Pe_{i,t} \times Pt_{i,t} + \\
& \sum_{p=2}^n \sum_{j=1}^m \sum_{j'=1}^m MC_p^{p-1}(j, j') \times ECM_{j,j'} \times TCM_{j,j'} + \\
& \sum_{p=2}^n \sum_{j=1}^m \sum_{t \in TM_j} \sum_{t' \in TM_j} TC_p^{j,p-1}(t, t') \times \\
& (TTC_{tl,tl'} \times ETC_{tl,tl'} + TCC_{c,c'} + ECC_{c,c'})
\end{aligned} \tag{5}$$

f_{EC} is a non-linear function. To linearize it, we can use the following equations:

$$y_{p,t}^j \times x_{i,p}^t = z \text{ S.t. } : z \leq x_{i,p}^t, z \leq y_{p,t}^j, z \geq y_{p,t}^j + x_{i,p}^t - 1, z \in \{0, 1\}$$

A complete description of the nine constraints associated to our problem are depicted in [7].

3 Proposed Approaches

In this section, we describe the adapted two evolutionary approaches, namely Dynamic-NSGA-II and NSGA-III. Two genetic operators, respectively crossover and mutation, are used as illustrated in Fig. 2 and Fig. 3. For clear descriptions of the considered coded process plan as well as the crossover and the mutation operators, refer to [8].

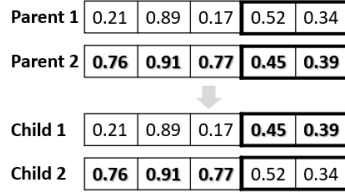


Fig. 2. Illustrative crossover operator

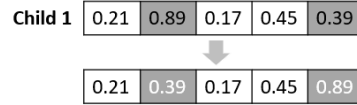


Fig. 3. Illustrative mutation operator

3.1 Dynamic Non Dominated Sorting Genetic Algorithm II (Dynamic-NSGA-II)

NSGA-II is an updated version of the non-dominated sorting genetic algorithm (NSGA) [9], well-known for solving multi-objective problems. The NSGA-II mechanism begins by ranking the solutions according to their non-domination score to get a set of Pareto front solutions. Then, the crowding distance technique, which guarantees diversity along the obtained Pareto front solutions, is applied on the last front to complete the next generation parent population size.

Nevertheless, the lateral diversity is not maintained. For better convergence, we proposed an adapted version of NSGA-II called Dynamic-NSGA-II. It uses a new diversity preservation technique called dynamic crowding distance, which can maintain lateral diversity and a uniform distribution of the Pareto front solutions. Algorithm 1 presents the main steps of the Dynamic-NSGA-II.

```

1: input data
2: initialize populationSize, iteration, pmutation, mutationRatio, pcrossover
3: randomize parentPopulation
4: for iter = 1 : iteration do
5:   generate childPopulation from parentPopulation
6:   population = parentPopulation  $\cup$  childPopulation
7:   F = fastNonDominatedSorting(population)
8:   for l = 1 : size(F) do
9:     if size(newPopulation)+size(Fl) < populationSize then
10:      newPopulation+ = Fl
11:     else
12:       DynamicCrowdingDistanceSorting(Fl)
13:       for k = 1 : size(Fl) do
14:         if size(newPopulation) < populationSize then
15:           newPopulation+ = Flk
16:         else
17:           break;
18:         end if
19:       end for
20:     end if
21:   end for
22:   parentPopulation = newPopulation
23: end for
24: return parentPopulation

```

3.2 Non Dominated Sorting Genetic Algorithm III (NSGA-III)

The NSGA-III's [10] framework is based on the NSGA-II. The major difference between the two algorithms is the selection mechanism. NSGA-III replaces the crowding distance with a reference point based niche mechanism, which can help spread out Pareto optimal fronts and improve population diversity. Note that, the same procedures (i.e., initial population, crossover and mutation operators) used for Dynamic-NSGA-II are being considered for NSGA-III. Algorithm 2 presents the main steps of NSGA-III.

```

1: Compute the number of reference points (H) to place on the hyper-plan
2: Generate the initial population randomly 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 Experimental Results and Analyses

The following experiments were implemented with a 4.0 GHZ Intel Core i7 processor and 16 GB RAM. The two approaches were 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. To analyze the Pareto solutions, two metrics, respectively Spacing metric [11] and inverted generational distance (IGD) [12], are used. Due to the space limitation, we replace Dynamic-NSGA-II by D-NSGA-II in the following tables.

For both Dynamic-NSGA-II and NSGA-III, the used parameters are as follows: Population-size= 40, number of iterations= 1000, probability of mutation= 90%, probability of crossover= 10% and mutation ratio= 0.3. Furthermore, to show the impact of the number of iterations on the quality of the Pareto fronts, instance 100-20bis refers to the situation where the number of iterations= 2000.

Table 2 presents the obtained numerical results, where two performance indicators are used, the CPU calculation time (in seconds) and the cardinality of the Pareto front (number of Pareto optimal process plans) of each instance.

Table 2. CPU time and cardinality of the Pareto fronts: D-NSGA-II vs NSGA-III

Instance	CPU(seconds)		Cardinality of the Pareto fronts	
	D-NSGA-II	NSGA-III	D-NSGA-II	NSGA-III
10-5	417.87	212.35	3	7
13-6	484.41	309.86	8	9
15-10	495.17	337.73	3	5
25-10	673.23	536.46	19	19
35-15	937.36	808.39	13	21
40-15	1057.23	950.05	16	26
50-20	1541.40	1485.96	20	13
100-20	3894.79	3740.28	16	13
100-20bis	15095.79	14281.22	44	37

Table 3 presents a comparison of the Pareto fronts obtained by Dynamic-NSGA-II and NSGA-III, where # Pareto front corresponds to the number of Pareto optimal process plans maintained in the new Pareto front (ie., contributions of Dynamic-NSGA-II and NSGA-III Pareto fronts in the new mixed Pareto front). The idea is to construct a new Pareto front based on the two Pareto fronts of respectively Dynamic-NSGA-II and NSGA-III. Moreover, Table 4 shows the obtained metric values.

Table 3. Performances comparisons: D-NSGA-II vs NSGA-III

Instance	Combination of the Pareto fronts of D-NSGA-II, NSGA-III			
	Total of cardinality	# Pareto front of D-NSGA-II	# Pareto front of NSGA-III	# Pareto front in common between D-NSGAI & NSGA-III
10-5	4	1	1	2
13-6	11	2	3	6
15-10	5	0	5	0
25-10	32	16	16	0
35-15	28	8	20	0
40-15	37	11	26	0
50-20	23	10	13	0
100-20	24	11	13	0
100-20bis	60	23	37	0

Table 4. Spacing metric and IGD values: D-NSGA-II vs NSGA-III

Instance	Spacing metric		IGD	
	D-NSGA-II	NSGA-III	D-NSGA-II	NSGA-III
10-5	695.13	128.72	64.28	48.36
13-6	40.26	108.74	36.05	36.05
15-10	2.89	2.24	17.03	10.44
25-10	328.76	613.40	524.31	426.61
35-15	302.38	264.62	357.54	761
40-15	340.74	179.48	192.93	310.27
50-20	265.18	321.57	229.98	230.36
100-20	805.53	5941.80	379.44	594.32
100-20bis	126.56	185.24	329.95	549.28

From the above three tables, we can distinguish three observations:

- Observations 1: From Table 2, we can see that, NSGA-III has better computational time, where Dynamic-NSGA-II has acquired more Pareto solutions for large instances.
- Observations 2: From Table 3, we observe that, NSGA-III completely dominates Dynamic-NSGA-II.
- Observations 3: From Table 4, we can conclude that Dynamic-NSGA-II algorithm has a great advantage in promoting diversity. Moreover, it indicates a major progression of the region covered by the Pareto front.

5 Conclusion and Perspectives

In this paper, we considered an environmental oriented multi-objective process plan generation problem in a reconfigurable manufacturing environment. We adapted two evolutionary approaches, respectively, Dynamic-NSGA-II and NSGA-III. To show the efficiencies of both approaches, some experimental results were realized and the obtained results were analyzed using three metrics respectively, spacing metric, inverted generational distance and cardinality of the mixed Pareto fronts.

For future works, shortly, 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. Moreover, other evolutionary-based approaches such as AMOSA, MOPSO, etc., can be adapted and compared.

References

1. Koren, Y.: The global manufacturing revolution: product-process-business integration and reconfigurable systems, vol. 80. John Wiley & Sons (2010)
2. Bensmaine, A., Dahane, M., Benyoucef, L.: A non-dominated sorting genetic algorithm based approach for optimal machines selection in reconfigurable manufacturing environment. *Computers & Industrial Engineering* 66(3), 519–524 (2013)
3. Zhang, H., Zhao, F., Sutherland, J.W.: Energy-efficient scheduling of multiple manufacturing factories under real-time electricity pricing. *CIRP Annals* 64(1), 41–44 (2015)
4. Stoycheva, S., Marchese, D., Paul, C., Padoan, S., Juhmani, A.s., Linkov, I.: Multi-criteria decision analysis framework for sustainable manufacturing in automotive industry. *Journal of Cleaner Production* 187, 257–272 (2018)
5. Touzout, F.A., Benyoucef, L.: Multi-objective sustainable process plan generation in a reconfigurable manufacturing environment: exact and adapted evolutionary approaches. *International Journal of Production Research* 57(8), 2531–2547 (2019)
6. Battaïa, O., Benyoucef, L., Delorme, X., Dolgui, A., Thevenin, S.: Sustainable and energy efficient reconfigurable manufacturing systems. In: Benyoucef, L. (ed.) *Reconfigurable Manufacturing Systems: From Design to Implementation*. SSAM, pp. 179–191. Springer, Cham (2020).
7. Khezri, A., Haddou Benderbal, H., Benyoucef, L.: Towards a sustainable reconfigurable manufacturing system (SRMS): multi-objective based approaches for process plan generation problem. *International Journal of Production Research* pp. 1–26 (2020)
8. Touzout, F.A., Benyoucef, L.: Sustainable multi-unit process plan generation in a reconfigurable manufacturing environment: A comparative study of three hybrid-meta-heuristics. In *Proceedings of IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA)*. vol. 1, pp. 661–668. IEEE (2018).
9. Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.: A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE transactions on evolutionary computation* 6(2), 182–197 (2002)
10. Deb, K., Jain, H.: An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints. *IEEE transactions on evolutionary computation* 18(4), 577–601 (2014)
11. Deb, K., Agrawal, S., Pratap, A., Meyarivan, T.: A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. In: *International conference on parallel problem solving from nature*. pp. 849–858. Springer, Berlin, Heidelberg. (2000)
12. Sierra, M.R., Coello, C.A.C.: Improving pso-based multi-objective optimization using crowding, mutation and ϵ -dominance. In: *International conference on evolutionary multi-criterion optimization*. pp. 505–519. Springer (2005)