Process and production planning for sustainable reconfigurable manufacturing systems (SRMSs): multi-objective exact and heuristic-based approaches

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Abstract
In today's competitive environments, companies need to be cost-effective, environmental-friendly, and social-friendly to deal with several challenges that exist in markets. In this context, reconfigurable manufacturing systems (RMSs) have emerged to fulfil these requirements. RMS is one of the attractive manufacturing paradigms. Machine components, software, or material handling units can be added, removed, modified, or interchanged as needed and imposed by the necessity to react rapidly and cost-effectively to changing. A multi-objective multi-product process and production planning problem in a sustainable reconfigurable manufacturing environment (SRMS) is considered in this paper. Three pillars of sustainability, respectively social, environmental, and economic are formulated and optimised. First, a linear mixed-integer model is proposed. Second, a Lagrangian relaxation-based approach is developed to solve the problem on the large scales, where an exact method is used to solve the problem in small and medium cases with GAMS software. To illustrate the applicability of the proposed approaches, some numerical examples and analyses are presented. Finally, a sensibility study of the problem according to some parameters is performed.

1 Context and motivations

In today's world, a manufacturing system must be cost-effective and environmentally harmless to acquire sustainability and compete with other rivals in the market. According to a visionary report of Manufacturing Challenges 2020 conducted in the USA, this trend will continue. One of the six grand challenges of this visionary report is "the ability to reconfigure manufacturing systems rapidly in response to changing needs and opportunities" [1]. Moreover, due to the escalation in fuel prices, the higher tariff for electrical use, and environmental legislation, the reduction in energy consumption and carbon footprint has become the need of the hour in the manufacturing sector. Through the latest decades, manufacturing technologies have evolved, and several terms have been introduced. In this regard, the term "industry 4.0" appeared in 2011 for the first time. And then [2] introduced nine decisive keys to implementing industry 4.0 in the manufacturing systems. In the concept of industry 4.0, they will work together to optimise several aspects of the production that can be seen in Fig. 1. As a result, advanced manufacturing solutions play a pivotal role in acquiring the industry 4.0 environment. It suggested that autonomous, cooperating industrial robots, and numerous integrated sensors and standardised interfaces are the main concepts of the advanced manufacturing solutions [3].

Reconfigurable manufacturing system (RMS) is one of the attractive manufacturing paradigms that can be helpful to combine with other methods to enable industry 4.0 [5, 6]. In this paradigm, machine components, machine software's, or material handling units can be added, removed, modified, or interchanged as needed and when imposed by the

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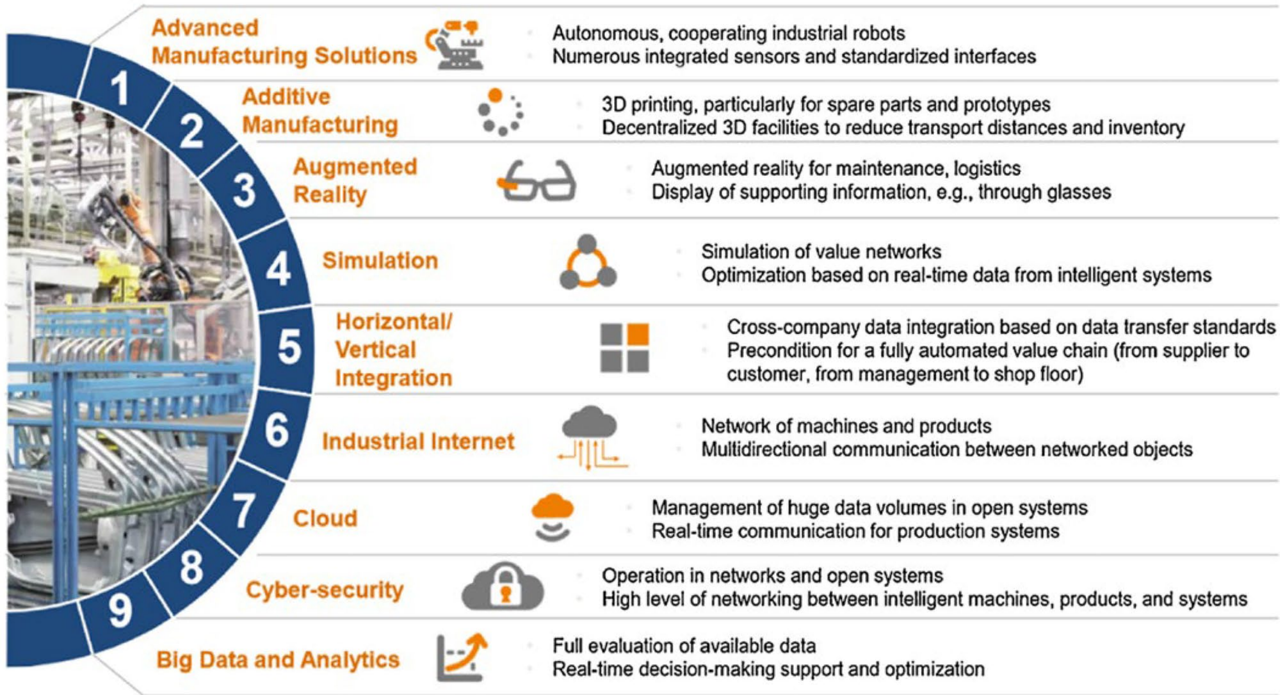


Fig. 1 Industry 4.0 in the manufacturing systems [4]

necessity to react and respond rapidly and cost-effectively to changing requirements. RMS is recognised as a convenient manufacturing paradigm for various productions and a flexible enabler for this variety [7]. RMS's concept is also introduced as a cost-effective response to markets' demands for responsiveness and customisation. This definition makes it easier to consider this system as a customised flexibility provider to prevent replacing by continuous improvement, upgrading, and reconfigured [1]. Therefore, it can be concluded that RMS can be one of the efficient factors to implement industry 4.0 in manufacturing plants.

Nowadays, manufacturing systems and RMSs have three main legs: cost, quality, and responsiveness, as noted in Fig. 2. The primary usage of responsiveness is that they enable the

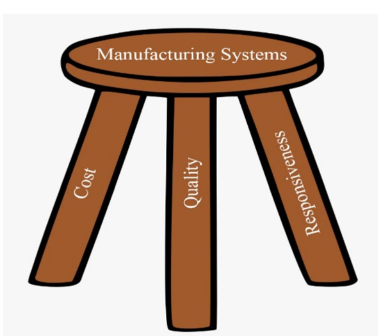


Fig. 2 Three goals of manufacturing systems [7]

system to react toward the market changes. Two significant changes in the markets are product demand changes and new products produced on existing manufacturing systems. To acquire rapid responsiveness and diminish reconfiguration time, every RMS has six main characteristics: scalability, convertibility, diagnosability, modularity, integrability, and customisation. Besides, the main features of the RMSs are modularity, changeability, and intelligent assembly systems that lead to contemplating them in this category. Hence, it indicates that RMSs are enablers of implementing the industry 4.0 environment now and in the future [8].

A sustainable future is the most crucial concern of human beings in today's world. This ability comprises happiness, health, education, job satisfaction, and so on. It relies on most aspects of human race life, such as social, environmental, and economical. Nowadays, numerous restrictions and laws are set pointing companies to lower the damage caused to the environment. Furthermore, they have to consider their operators' health condition and the effects of harmful materials and remnants on their bodies. Besides, sustainable manufacturing is used to improve human life in terms of satisfaction and other lifestyle matters. RMS can meet these challenges due to its flexibility and integrability. Moreover, it is thought to be one of the most suitable paradigms with sustainability requirements [9]. Therefore, we can define SRMS rely on as "a RMS system that can transform materials without (i) greenhouse gas emissions and (ii) use of unsustainable or toxic materials or (iii) produce waste and (iv) respect the human being social life".

Currently, RMS is an attractive researching field for both researchers and industrials. Hence, many works of art in such fields as process planning, production planning, layout optimisation, design, and production schedule can be seen. In this paper, new approaches toward the sustainable multi-objective RMS are considered, where the first results are presented [10]. The combination of process planning and production planning in the sustainable area happened for the first time in this work. In the production planning area of working, it is crucial to answering the market's demands by considering the limits of the whole system. In the process planning part, the best sequences for the production of several products are considered. The aim is to minimise the total cost function, minimise the harmful effects of the gases and liquids on the human body and maximise social benefits as social sustainability. This study's innovations consider both process planning and production planning in a reconfigurable environment, involving all sustainability facets and several product production sequences. More specifically, the main contributions of the paper are:

1. Consider social sustainability factors in a reconfigurable manufacturing environment.
2. Consider environmental sustainability factors in a reconfigurable manufacturing environment.
3. Consider production and process planning together in a reconfigurable manufacturing environment.
4. Propose a linear multi-objective mixed-integer mathematical formulation.
5. Develop exact and heuristic solving approaches and compare them.
6. Address sensitivity analyses of the problem according to some parameters.

The rest of the paper is organised as follows: Section 2 reviews some related sustainability works in manufacturing systems, process planning in manufacturing systems, and production planning in manufacturing systems. Section 3 describes the problem under consideration and its mathematical formulation. Section 4 presents the proposed exact and heuristics-based approaches. Section 5 illustrates some numerical examples and analyses the obtained results in different scales. Section 6 shows the sensibility of the problem according to some parameters. Section 7 concludes the paper and outlines some future work directions.

2 Literature review

As one of the newest paradigms, RMS has demonstrated outstanding potential for further researches. This section briefly reviews some research works in sustainability, process planning, and production planning in manufacturing systems and RMS.

2.1 Sustainability and RMS

In the RMS concept, several different facets of sustainability, as social, environmental, and economic, are considered to stay competitive from the decision maker's perspective. Although the RMS's first definition appeared in 1994, the correlation between an RMS production plan and the sustainable area is novel. It is easy to find many research works in economics and the relationship between RMS and sustainable working areas; however, few surveys concentrated on the quantitative manners of social impacts on a sustainable RMS. Besides, most of the research works that focus on the environmental aspects of the RMS ignore other aspects [11].

A significant portion of papers focuses on the costs, objective functions or added value of economic sustainability objectives. Therefore, it is essential to recognise different costs in the manufacturing system. Raw materials, manufacturing, transportation, and operations are the most critical costly elements in manufacturing systems [12]. Besides, operators' salary and cost can consider separately from the costs of final products. In the RMS, the more reconfigurability, the more economical and environmental sustainability can achieve. It means, if a workshop can elevate this matter for the machines, they will be able to increase their final profit and reduce final costs [13].

Several optimisation methods have been used in the multi-objective scenario to find the best sequences of the process plans' operations. In the concept of sustainable RMS, Touzout and Benyoucef [14] proposed a multi-objective MILP model with two adapted versions of the well-known non-dominated sorting genetic algorithm (NSGA-II) and archived multi-objective simulated annealing (AMOSA). Greenhouse gases and the amount of harmful gas emissions, and the cost of manufacturing are minimised. Khezri et al. [15] used augmented ε-constraint (AUGECON) to minimise the total production costs, the total completion time, and the total energy consumption during the manufacturing process. Moreover, Khezri et al. [16] developed a sustainable RMS that responds to customer demands cost-effectively and environmentally friendly. In this paper, the authors provide a multi-objective problem where production cost, production time, and manufacturing liquid hazardous and energy consumption are studied and minimised. In this regard, an AUGECON method and adapted versions of NSGA-II and SPEA-II are used and compared to solve the problem.

Nevertheless, designing reconfigurable manufacturing systems can have several elements of social sustainability. Such elements as being user-friendly and ergonomics can be considered the machines using matters, and some other social aspects such as the job opportunity created by the systems for the people in the neighbourhood of the company are considered system matters. If the system is simple for the operator to program and support manual operations, we can call it user-friendly. Moreover, the operation environment, layout, and so on, can affect the operators' mental and physical health condition in the long term is considered ergonomics [17].

2.2 Sustainability in manufacturing systems

The Cambridge dictionary defines a sustainable manufacturing system as: "the idea that goods and services should be produced in ways that do not use resources that cannot be replaced and that do not damage the environment". Another useful definition of sustainability by [18] is: "is not an absolute, independent of human conceptual frameworks. Rather it is always set in the context of decisions about what type of system is to be sustained and over what spatiotemporal scale". Therefore, it is possible to mention that sustainability is a leading force in the industries in the twentieth-first century, according to the world changes during centuries.

Sustainability is considered an essential facet for future manufacturing, so many papers and reviews are dedicated to sustainable manufacturing. According to Malek and Desai [19], developing countries had significant progress in implementing sustainability through their automobile industries. Moreover, one of the best choices for today's companies and market owners is sustaining their market existence in social, environmental, and economic aspects. The hopeful prospect is that by implementing sustainability for all the elements mentioned above, they can balance their market and achieve their goals. Another review study proposed an analytical framework of the life cycle sustainability in the manufacturing systems [20]. Besides, the authors tried to find the relationship between socio-economic reciprocation and social exchange theories in a sustainable environment.

For the sustainable manufacturing paradigm, the decision-maker can play a pivotal role in several aspects, so it is essential to pay the way for the decision-maker. For supporting decision-making, it is essential to provide a holistic understanding of advanced scientific analysis methodologies in all aspects of sustainability [21]. Moreover, the lack of knowledge to understand the differences between social, environmental, and economic sustainability can impede the future growth of sustainability and make decision-making harder at the unit process and enterprise levels. Therefore, using some methods that clarify the border of sustainability matters from each other in manufacturing systems will help us solve the complicated decision-making problems [22]. Environmental factors are considered as the emissions of greenhouse gases and other harmful materials in the environment. Wastes of the production sites can be considered one of the most important factors of environmental sustainability. It is possible to reuse some parts of the production part's waste, but it is essential to set the tools in the appropriate path and save the critical part of the materials before being completely unusable [23].

From the manufacturing and service point of view, it is essential to design products that rely on sustainability matters. Moreover, business development sustainability is crucial in the manufacturing sustainability perspective [24]. They are two other factors in environmental sustainability. They are management and organisational culture and energy consumption. The management and organisational culture indicators are the authorities' roles on the final manufacturing system sustainability [25]. Besides, for energy consumption, the energy consumption from the vehicles' usage in the working environment can be an example of this matter [13]. In the multi-objective context, Zahiri et al. [26] tried to maximise job opportunities in the considered zone for unemployed people.

Moreover, the area with the maximum chance of getting more operators to employ is selected as the optimal one. Some other papers in the multi-objective area consider this procedure to bring social sustainability matters in the mathematical formulation [27]. Finally, we can conclude that manufacturing sustainability is the most critical part of sustainability implementation in today's world [28].

2.3 Process and production planning in manufacturing

A process plan is a bridge between product and resources and operations paths to achieve the final products. Therefore, it is essential to find the best operations sequences for every single unit in the manufacturing environment [29]. Moreover, it is essential to consider other aspects of the production plan to perform operations and sequences better. Such aspects as scheduling units or production planning can be helpful [30].

Musharavati and Hamouda [31] proposed simulated annealing (SA)-based algorithms to deal with the process planning problem in a reconfigurable environment. They developed several variants of the SA algorithms, a variant of the basic SA algorithm, a variant of the SA algorithm coupled with auxiliary knowledge, and a variant of the SA algorithm implemented in a quasi-parallel architecture. The obtained experimental results showed the superiority of the variants in comparison to a basic SA algorithm. Maniraj et al. [32] proposed a two-phase-based ant colony optimisation approach to solve a single product flow line's process plan generation problem in a reconfigurable context. In the first phase, the priority-based encoding technique is applied to find feasible operation clusters. In the second phase, the ant colony technique is used to minimise the total cost of the RMS. A case study is presented to demonstrate the applicability of the developed approach.

In a multi-objective context, Chaube et al. [30] and Bensmaine et al. [33] proposed an evolutionary-based approach to solve the single unit process plan generation problem. Chaube et al. [30] adapted the NSGA-II, where two objectives are minimised, respectively, the total completion time and the total manufacturing cost. Bensmaine et al. [33] integrated the process plan generation with the design problem using the same approach. Haddou Benderbal et al. [34] proposed a new flexibility metric to generate efficient process plans by integrating unavailability constraints of the selected machines. The resulting multi-objective problem is solved using an adapted version of NSGA-II. Recently, Khettabi et al. [35] addressed the 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, they proposed four adapted versions of NSGA-II, NSGA-III, weighted genetic algorithms (WGA), and random weighted genetic algorithms (RWGA). Furthermore, three metrics, respectively hypervolume, spacing metric, and cardinality of the mixed Pareto fronts, were used to demonstrate the performances of the four approaches. The results showed the superiority of NSGA-III in solving the problem.

Production planning links several segments in a manufacturing environment, such as operations scheduling, output capacity, final product quality, etc. Furthermore, quality control and process planning can play a decisive role in quantitative matters' decision-making [36]. In this context, few research works have considered multiple production systems' implications to produce a specific final product. Liu et al. [37] presented a mixed-integer stochastic programming model for manufacturing systems. They introduced an effective tool for optimising the production plans rely on the decision-maker's point of view.

Recentely, Kaltenbrunner et al. [38] considered the production planning for highly automated pallet production. They proposed a heuristic solution approach to solve the cutting stock problem with a constraining open stack problem occurring at the beginning of pallets' production, the saw, and the downstream stacking robots. The objective is to minimise the waste of material and ensure a continuous production flow at the pallet production site. Okpoti and Jeong [39] presented a reactive, decentralized coordination mechanism facilitating collaborative production planning decisions. More specifically, the mechanism determines a plan before the start of production, which is re-optimized in case any dynamic events occur after the production horizon. To demonstrate the applicability of the developed mechanism, they designed and implemented a cyber-physical production system prototype that incorporates all the existing fundamental elements of the smart factory. The obtained results are promising in terms of work-in-process, delayed demand, system throughput on average in dynamic environments.

2.4 Research split

From the above literature review, it is probable to find some gaps in this moot point. In the prior studies of RMS, the authors just focused on the production cycles of the RMS. It is noted that none of the previous researchers concentrated on the several visions of the sustainability indicators such as social, environmental, and economic in tandem. Besides, the process planning methods were not combined with the production planning aspects in a sustainable environment. Moreover, we can conclude that the combination of process and production planning in a sustainable environment is an exciting and new RMS topic. Therefore, the gap can be named as implementing all aspects of sustainability in an RMS environment and discovering the best production quantity and process sequences rely on the innovations (Table 1). The main innovations of the article according to the mentioned problem are depicted as follows:

- We address the harmful impacts of the machines and materials on the environment.
- We consider the social impact of RMS.
- We consider a multi-product production cycle in the presented period.
- We model and propose a multi-objective mathematical formulation of an SRMS.
- We develop exact and heuristic solving approaches and compare them.
- We address sensitivity analyses of the problem according to some parameters.

3 Problem description and formulation

3.1 Problem description

Regarding the research gap found in the previous sections, this problem considers all sustainability matters in an RMS environment. Three different objectives contain social, environmental, and economic aspects. For economic sustainability, a cost function is proposed. The cost function includes RMS's production cost during activities on the raw material to make the final specific part families and related production costs. For environmental sustainability, harmful gasses and liquids remnants from the machines during production are considered. For social sustainability, the local considered employment rate and the social benefit associated with the generation of employment in the RMS environment zone are maximised.

Table 1 Literature background of RMS

References	Objective		Sustainability indicator			Cost function		Product		Time	Production planning	Process planning	Optimisation methods
	Single objective	Multi-objective	Economic	Environmental	Social	Production	Sustainability	Single	Multiple				
[41]	✓					✓			✓	✓			GA
[42]	✓					✓			✓	✓	✓		TS
[43]	✓	✓				✓			✓	✓		✓	GA
[33]	✓					✓		✓		✓		✓	NSGA-II
[31]	✓					✓			✓			✓	SA
[32]	✓					✓		✓				✓	AC
[13]	✓					✓			✓	✓	✓	✓	CPLEX
[44]	✓		✓			✓	✓			✓	✓		CPLEX
[40]	✓					✓			✓	✓	✓		CPLEX
[34]		✓				✓				✓		✓	NSGA-II
[45]	✓					✓				✓		✓	AMOSA and TOPSIS
[14]		✓		✓		✓		✓		✓		✓	NSGA-II, AMOSA, and I-MOILP
[46]		✓		✓		✓		✓		✓		✓	NSGA-II, RSUPP, LSSUPP, and ABILS
[47]		✓		✓		✓	✓	✓		✓		✓	WGP
[48]		✓				✓			✓	✓		✓	MOSOMA
[49]	✓					✓			✓	✓			LP-Solver Optimizer
[15]		✓		✓		✓	✓	✓		✓		✓	AUGECON
[16]		✓	✓	✓		✓	✓	✓		✓		✓	AUGECON, NSGA II, SPEA II
[50]	✓					✓			✓				UGF
This paper		✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	Lagrangian relaxation-based approach

AC ant colony, *TS* Tabu search, *GA* genetic algorithm, *NSGA-II* non-dominated sorting genetic algorithm II, *SA* simulate annealing, *LP* linear programming, *AMOSA* archived multi-objective simulated annealing, *TOPSIS* technique for order of preference by similarity to ideal solution, *RSUPP* repetitive single-unit process plan, *LSSUPP* local search on single-unit process plans, *ABILS* archive-based iterated local search, *WGP* weighted goal programming, *MOSOMA* multi-objective self-organizing migrating algorithm, *AUGECON* augmented ε-constraint, *SPEA-II* strength Pareto evolutionary algorithm II, *UGF* universal generating function

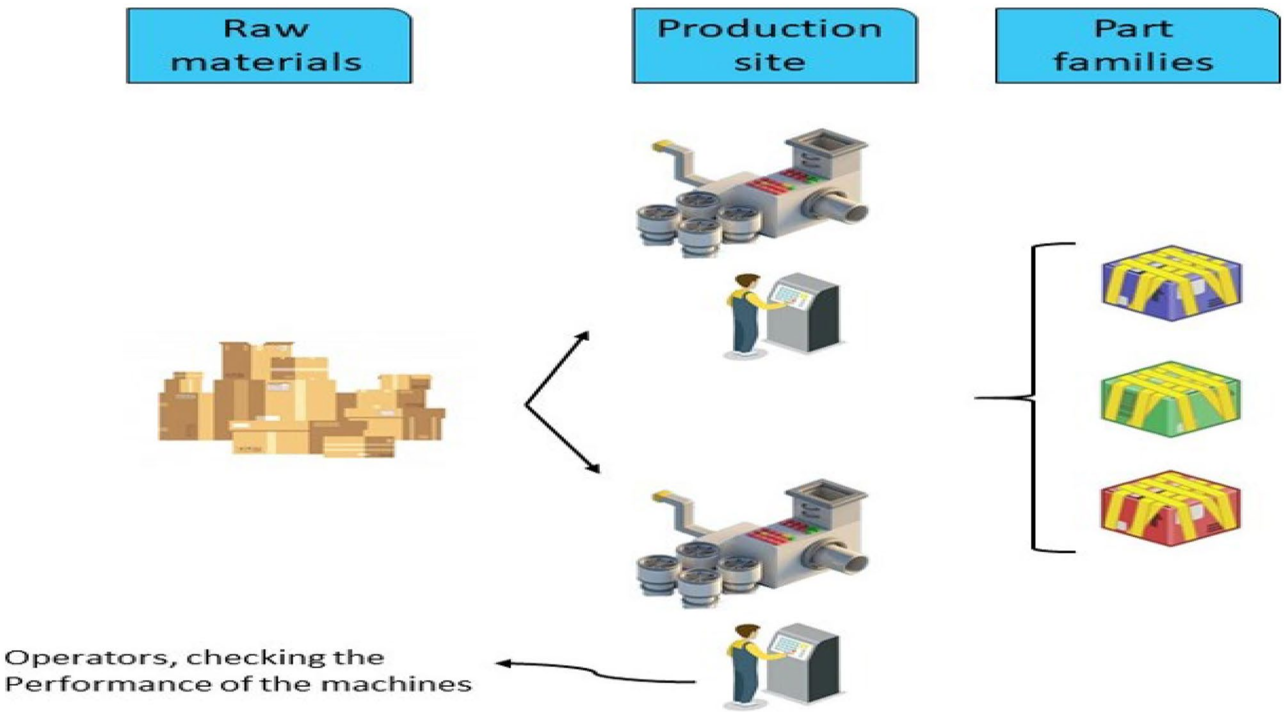


Fig. 3 Graphical abstract of the problem

In our case, the final products are from the same part families, and the manufacturing process involves receiving raw materials and turning them into final products. We try to determine the best process and production planning. Process planning aims to obtain the optimum sequences of the machines, configurations, and operations during manufacturing. Moreover, production planning aims to determine the optimum quantities of products that should be produced. Figure 3 shows the graphical abstract of the problem.

As depicted in Fig. 3, the raw materials come to the manufacturing system. Several activities regarding the process planning and production planning have to be done to provide specific final part families. The machines can process multiple products, subject to configuration changes. Nevertheless, during this process, machines will emit dangerous gases and liquids. In our case, each product from the part family can have several process plans; however, each part family will have the same optimal sequences of operations. The final products' quantities have to satisfy the markets' demands in the considered time window. Furthermore, during the production process, the operators have to stay near the machines to visually inspect the machines' work and prevent any possible risks and failure. To maximise the utility of the company zone, in the social objective, it tries to employ operators from the neighbourhood to elevate job opportunities in the company's zone.

As mentioned previously, reconfigurable machines can manufacture multiple products from the same part family. During the production time, there can be some changes, such as configuration changes. Moreover, other production orders can intervene to answer the market demands to find the most profitable and cost-effective process and production plans during a one-time horizon. There is no shortage of raw materials, and the final products have no inventory costs. For each product, the process plan is a matrix with *n* columns (number of operations) and three rows (operations, machines, and configurations). Table 2 presents examples of process plans of products P1 and P2 from the same part family that should be read from left to right. It represents the sequence of operations to be performed, where each column illustrates the performed operation, machine, and configuration. For example, to manufacture P1, operation 2 denoted by Op_12 is realized by machine M1 using configuration H3.

The system can use the optimal operations sequences and deploy the production plans to answer market demands of products P1 and P2 (Fig. 4). Moreover, P1 and P2 have the same number of operations (five operations) related by the same precedence graph of Fig. 4 (i.e. same part family). However, Op_11, Op_12, Op_13, Op_14, and Op_15 of P1 are a little bit different from Op_21, Op_22, Op_23, Op_24, and Op_25 of P2. The differences between products are due to the operation functionalities, which are related to machines and configurations.

Table 2 Simple examples of generated process plans

P1	Operations	$Op_1 1$	$Op_1 2$	$Op_1 4$	$Op_1 3$	$Op_1 5$
	Machines	M1	M1	M1	M2	M2
	Configuration	H2	H3	H2	H1	H1
P2	Operations	$Op_2 1$	$Op_2 3$	$Op_2 2$	$Op_2 4$	$Op_2 5$
	Machines	M2	M2	M2	M1	M1
	Configuration	H3	H1	H1	H2	H2

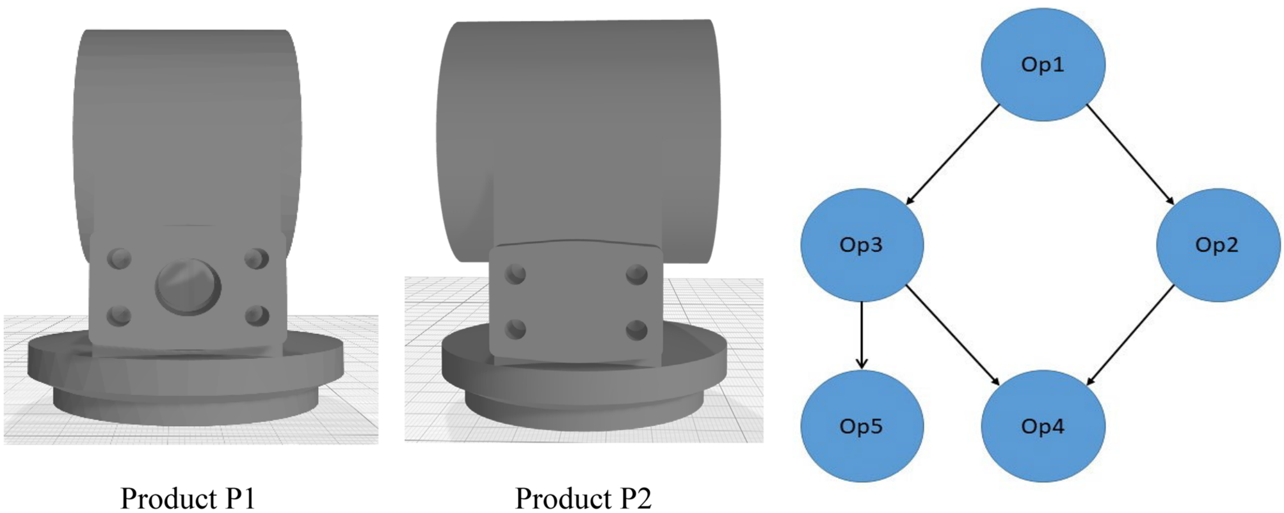


Fig. 4 An illustrative products schemas and operations precedence graph

3.2 Model assumptions

The proposed model is based on the following assumptions:

Assumption 1: Operators check the machine's processing and do visual examinations for the final products.
Assumption 2: Operators use special equipments and are protected from harmful gases during the visual examinations.
Assumption 3: Multiple products can be produced.
Assumption 4: Each product can follow several process plans using several reconfigurable machines.
Assumption 5: The market demands are deterministic.
Assumption 6: During the process, no failure will happen.
Assumption 7: It is necessary to produce more than the markets' demands.
Assumption 8: There is no storage cost of the products.
Assumption 9: During the production, the harmful gases emit and affect the operator's bodies' health.
Assumption 10: The problem is considered in a one-time window.

3.3 Mathematical formulation

The following notations are used:

Parameters	
i, i'	Index of operations
j, j'	Index of positions in the processing sequence
p	Index of products in part families
m, m'	Index of machines
h, h'	Index of configurations
op	Number of operations
con	Number of configurations
$prod$	Number of part family products
mac	Number of machines
pos	Number of positions
BM	A big number
T_{mp}	Average cycle time of machine m to operate on product p
CAP_{mp}	Maximum capacity of machine m to operate on product p

Parameters	
i, i'	Index of operations
$PCAP$	Production capacity
DEM_p	Demand of part family products p in the considered period
TP_p	Total production time of part family products p
AC_{ph}	Assignment cost of part family products p in configuration h
$CM_{jj'm}$	Changeover cost from position j' to position j in machine m per time unit
PC_{ijp}	Processing cost of operation i on the part family products p at position j per time unit
$TM_{jj'm}$	Changeover time from position j' to position j in machine m
PT_{ijp}	Processing time of operation i on the part family products p at position j
PR_i	Set of predecessors of operation i
QC_{ph}	Production cost of part family products p in configuration h
$EL_{i,j}$	Harmful liquid remnants of the operation i at position j
$EG_{i,j}$	Harmful gases emission of the operation i at position j
$l_{i,j}$	Required liquid for operation i at the position j
L	Total available liquid
UR_m	Rate of unemployed that can work on machine m in the potential location
SL	Operators' average salary
Decision variables	
x_{ijh}^{p}	= 1 if operation i is processed at position j, to produce part family product p, using the configuration h = 0 otherwise
y_{jh}^{mp}	= 1 if machine m is at the position j, to produce part family product p, using the configuration h = 0 otherwise
$v_{jj'}^{mp}$	= 1 if there is a change in machine number m between the position j' and j, to produce part family product p = 0 otherwise
w_m	Number of assigend operators to machine m

Parameters	
i, i'	Index of operations
Q_p	Production quantity of product p
AS_{ph}	Assignment matrix of part family product p to configuration h
Z_1	Cost function
Z_2	Environmental pollution function
Z_3	Social sustainability function

The following multi-objective model is used to select the best process and production planning according to sustainability indicators. The objective functions and constraints are defined as follows:

$$\mathrm{Min}Z_1 = \sum_{i=1}^{op}\sum_{j=1}^{pos}\sum_{p=1}^{prod}\sum_{h=1}^{con} PT_{ijp} \times PC_{ijp} \times x_{ijh}^{p} + \sum_{j=1}^{pos}\sum_{j'=1}^{pos}\sum_{m=1}^{mac}\sum_{p=1}^{prod} v_{jj'}^{mp} \times TM_{jj'm} \times CM_{jj'm} + \sum_{h=1}^{con}\sum_{p=1}^{prod} Q_p \times QC_{ph} + \sum_{h=1}^{con}\sum_{p=1}^{prod} AS_{ph} \times AC_{ph} + \sum_{m=1}^{mac} w_m \times SL \tag{1}$$

$$\mathrm{Min}Z_2 = \sum_{i=1}^{op}\sum_{j=1}^{pos}\sum_{p=1}^{prod}\sum_{h=1}^{con} PT_{ijp} \times (EL_{i,j} + EG_{i,j}) \times x_{ijh}^{p} \tag{2}$$

$$\mathrm{Max}\, Z_3 = \frac{\sum_{m=1}^{mac} (UR_m \times w_m)}{\sum_{m=1}^{mac} UR_m} \tag{3}$$

Subject to:

$$\sum_{i=1}^{op}\sum_{p=1}^{prod} x_{ijh}^{p} = 1 \quad \begin{array}{l}\forall j \in [1, \dots, pos] \\ \forall h \in [1, \dots, con]\end{array} \tag{4}$$

$$\sum_{j=1}^{pos}\sum_{p=1}^{prod} x_{ijh}^{p} = 1 \quad \begin{array}{l}\forall i \in [1, \dots, op] \\ \forall h \in [1, \dots, con]\end{array} \tag{5}$$

$$\sum_{h=1}^{con} x_{ijh}^{p} \times |PR_i| \leq \sum_{i'=1}^{op}\sum_{j'=1}^{pos}\sum_{h'=1}^{con} x_{i'j'h'}^{p} \quad \begin{array}{l}\forall i \in [1, \dots, op] \\ \forall j \in [1, \dots, pos] \\ \forall p \in [1, \dots, prod]\end{array} \tag{6}$$

$$\sum_{h=1}^{con} y_{jh}^{mp} = 1 \quad \begin{array}{l}\forall j \in [1, \dots, pos] \\ \forall m \in [1, \dots, mac] \\ \forall p \in [1, \dots, prod]\end{array} \tag{7}$$

$$y_{jh}^{mp} \geq x_{ijh}^{p} \; \forall i \in [1, \dots, op] \forall j \in [1, \dots, pos] \forall m \in [1, \dots, mac] \forall p \in \left[1, \dots, prod\right] \forall h \in [1, \dots, con] \tag{8}$$

$$\sum_{i=1}^{op}(x_{ijh}^{p}+x_{ij-1h}^{p})\le v_{jj'}^{mp}+1$$
$$\forall j,j'\in[1,\dots,pos]\ \forall m\in[1,\dots,mac]\ \forall p\in[1,\dots,prod]\ \forall h\in[1,\dots,con] \tag{9}$$

$$\sum_{i=1}^{op}\sum_{j=1}^{pos}x_{ijh}^{p}\times AS_{ph}\times con\ge q^{p}\quad \begin{matrix}\forall p\in[1,\dots,prod]\\ \forall h\in[1,\dots,con]\end{matrix} \tag{10}$$

$$Q_p=DEM_p\ \ \forall p\in[1,\dots,prod] \tag{11}$$

$$Q_p\times T_{mp}\le CAP_{mp}\quad \begin{matrix}\forall p\in[1,\dots,prod]\\ \forall m\in[1,\dots,mac]\end{matrix} \tag{12}$$

$$AS_{ph}-AS_{ph'}+\left(1-v_{jj'}^{mp}\right)\mathrm{BM}-1\ge 0$$
$$\forall j,j'\in[1,\dots,pos]\forall m\in[1,\dots,mac]$$
$$\forall p\in[1,\dots,prod]\forall h,h'\in[1,\dots,con] \tag{13}$$

$$\sum_{p=1}^{prod}Q_p\times TP_p\le PCAP \tag{14}$$

$$w_m\ge 1\ \ \forall m\in[1,\dots,mac] \tag{15}$$

$$\sum_{i=1}^{op}\sum_{j=1}^{pos}\sum_{p=1}^{prod}\sum_{h=1}^{con}x_{ijh}^{p}\times PT_{ijp}\times l_{i,j}\le L \tag{16}$$

$$x_{ijh}^{p}\in\{0,1\}\ y_{jh}^{mp}\in\{0,1\}\ v_{jj'}^{mp}\in\{0,1\}$$
$$\forall i\in[1,\dots,op]\ \forall j\in[1,\dots,pos]\ \forall m\in[1,\dots,mac]$$
$$\forall p\in[1,\dots,prod]\ \forall h\in[1,\dots,con] \tag{17}$$

Equation (1) is the cost function. Equation (2) is the environmental sustainability function. Equation (3) is the social sustainability function that is a normalized equation. The denominator of each term in the equation is the sum of parameters representing the maximum possible value. For example, $\sum_m UR_m$ corresponds to the sum of add value factor for the rate of employment. Constraint (4) ensures that all the configurations can have access to all the positions. Constraint (5) indicates that each operation is processed once for part families in each configuration. Constraint (6) states that each operation is processed if all of the predecessors' operations are already finished. Constraint (7) illustrates that each configuration contains machines and part families. Constraint (8) ensures that if operation i performed at position p, machine m, and configuration h are required. Constraint (9) shows that if there is a change in the machines between the positions or not during the production. Constraint (10) claims that the number of final products in each part families are according to configurations assignment. Constraint (11) indicates that it is crucial to answer all customer demands. Constraint (12) introduces the production capacities. Constraint (13) uses to prevent the backward direction of production flows. Constraint (14) indicates that the amount of production time should not exceed the available time. Constraint (15) shows that each machine should have assigned to at least one operator. Constraint (16) considers the limitation of the total required liquid during the production process. Constraint (17) determines the types of variables.

4 Proposed approaches

In this section, we discuss several approaches proposed to solve the developed mathematical model. According to the Lp-metric objective functions and constraints in the mathematical formulation, we can solve our problem as a single-objective mathematical formulation by baron solver [51] using GAMS Solver. Besides, it helps the decision-maker to choose between several objectives according to his preference. Furthermore, to implement a Lagrangian relaxation (LR) based approach, abounded objective approach is developed. We used the Lp-metric-based approach in the first step because there will be no choices between the weights of the objective functions for the decision-maker in the bounded objective function in the managerial point of view. However, in the Lp-metrics-based approach, the decision-maker can have a pivotal role in choosing each objective's weight. The LR-based approach is a heuristic method that approximates a problematic model with several constraints optimise solution relies on a more straightforward relaxed problem. In the last part of this section, we used a sub-gradient based-method to update the LR-based approach co-efficiency.

4.1 Lp-metric based approach

There are many multi-objective programming ways to consider the decision-maker's point of view and solve the problems. For instance, ε-constraint and goal programming comprises programming (Yousefi et al., 2017). In this paper, we prefer programming because of a couple of reasons. First of all, the primary purpose of using weighted sum programming is that it is possible to give the decision-maker enough freedom to consider each weight he wants to the objective functions that are improbable in other procedures. Furthermore, according to Babbar and Amin [52], the final answer can be more exact for our paper with this method.

For the proposed model, three objective functions are, respectively Z_1, Z_2, and Z_3. The model is solved separately for each of the three objectives with the LP-metrics base approach. The optimum value of each objective function is Z_1^*, Z_2^*, and Z_3^*. The mentioned single objective function can now be formulated as follows (18):

$$\text{Min } Z_4 = weight_1 \times \left(\frac{Z_1 - Z_1^*}{Z_1^*}\right) + weight_2 \times \left(\frac{Z_2 - Z_2^*}{Z_2^*}\right) - weight_3 \times \left(\frac{Z_3 - Z_3^*}{Z_3^*}\right) \tag{18}$$

where the weights are related by Eq. (19):

$$\sum_{i=1}^{3} weight_i = 1 \tag{19}$$

4.2 Bounded objective function

In this paper, the bounded objective function method is used to make the multi-objective method into the objective function. There are two reasons to choose this method in this part of the paper. First of all, it will pay for implementing the LR-based approach in the next section. Furthermore, this method makes the solving method more manageable, and it is not practical enough as the decision-maker's point of view comprises programming. In this method, one of the objective functions is considered the primary objective function, and the other ones are considered the constraints with assigned upper and lower bounds [53].

In our problem, the most critical objective function is the cost function. The payoff table calculates the upper and lower bounds of the other objectives in the constraint. The bounded objective function is as follows:

$$Min\ Z_1 \tag{20}$$

Subject to:

$$LB_i \leq Z_i \leq UB_i \quad i = 2, 3 \tag{21}$$

EQS (4-17) (4-17)

where Z_1 is the first objective function and LB_i and UB_i are the bounds of the ith objective function. Moreover, it will be solved with the rest of the objective functions as a single-objective model.

4.3 Lagrangian relaxation-based approach

It is possible to solve small- and medium-scale problems with GAMS solver. Nevertheless, solving large-scale problems, such as our problem, can be so time-consuming for the GAMS to solve our problem. The Lagrangian relaxation-based method has been extensively adopted in different fields such as manufacturing and supply chain management to solve large-scale problems and complex mathematical formulation. Zheng et al. [54], Heidari-Fathian and Pasandideh [53], and Yousefi-Babadi et al. [55] are some examples of the usage of the Lagrangian relaxation based method in supply chain management. Hong et al. [56] adopted this method in the manufacturing systems. Regarding the efficiency of this approach in the several problems, it has been adapted to our problem.

The proposed mathematical formulation is a mixed-integer programming model for an NP-hard problem [5]. As mentioned above, commercial mathematical programming software cannot solve an NP-hard model like our RMS model on large scales, so it is essential to implement an algorithm to solve the problem. In the LR-based approach, it is so important to choose the best constraint for the relaxation part. In this paper, we started to relax the constraints that can be more time-consuming than the others separately. Constraints (4), (5), and (10) are relaxed one by one, and the model ran to show the best one for selecting as the relaxed constraint. Besides, to compare them, the CPU time has been obtained as illustrated in Table 3.

As it is noted in Table 3, constraint (5) has been selected for the relaxation part in this approach. Therefore, the mathematical formulation can be written as follows:

$$Z_4 = MinZ_1 - \sum_{i=1}^{op} \sum_{h=1}^{con} \partial_{ih} \left[\sum_{j=1}^{pos} \sum_{p=1}^{prod} x_{ijh}^p - 1 \right] \quad \begin{array}{l} \forall i \in [1, \dots, op] \\ \forall h \in [1, \dots, con] \end{array} \tag{22}$$

subject to:

$$LB_2 \leq Z_2 \leq UB_2 \tag{23}$$

$$LB_3 \leq Z_3 \leq UB_3 \tag{24}$$

Eqs. (4), (6–17) (4), (6–17)

where ∂_{ih} is the LR-based approach coefficients and its' value is free and Z_4 is the objective function.

Table 3 Results of constraints selection approach

Relaxed constraint number	CPU time
4	1.470
5	1.365
10	1.480
Without relaxation	1.580

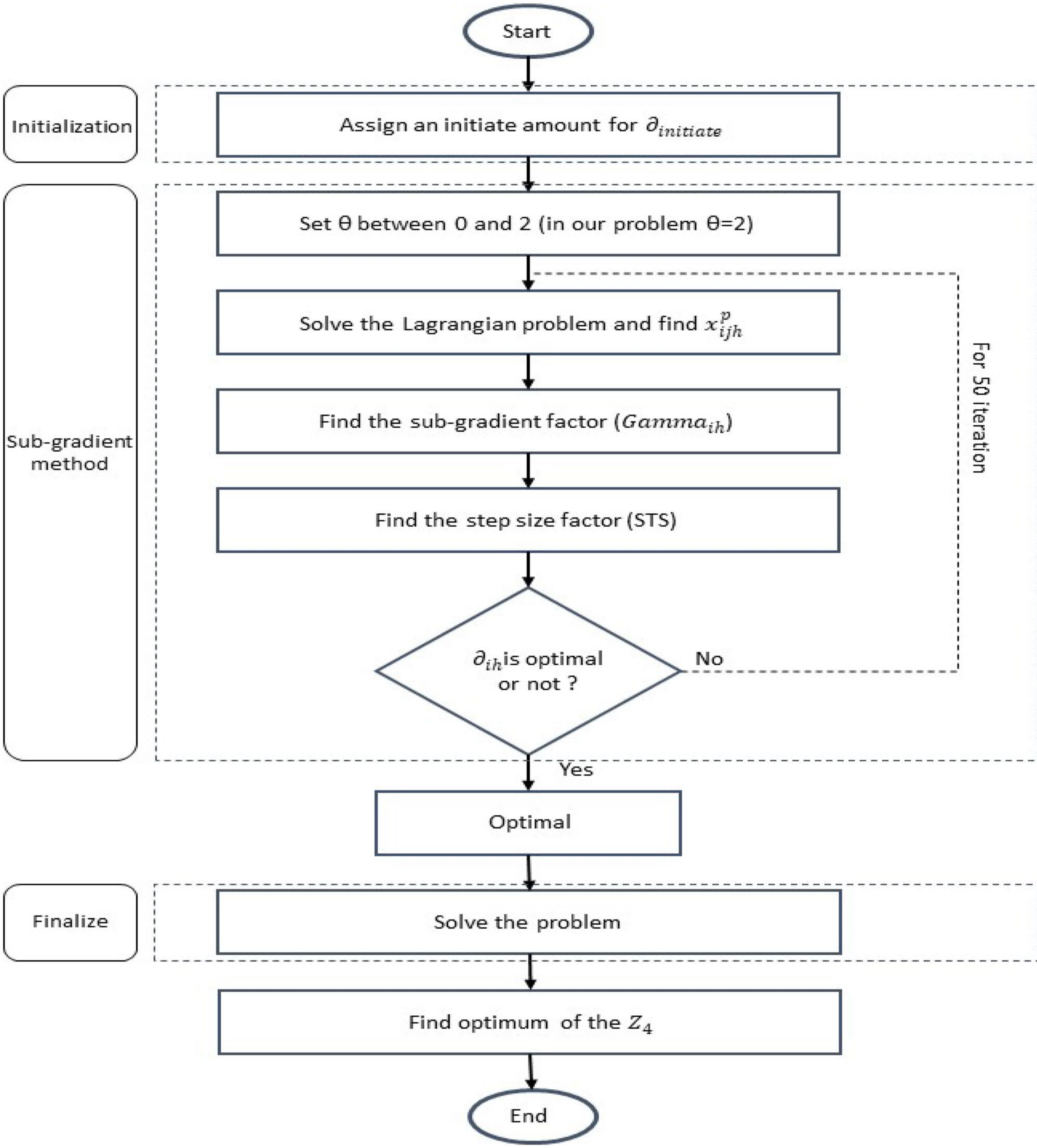


Fig. 5 Flowchart of the algorithm

4.4 Sub-gradient based-method

Several methods such as sub-gradient, coefficients correction, bundle and cutting plane, and column generation can help update the LR-based approach coefficient. According to Fisher [57] and literature review, the sub-gradient is a suitable method with a high-performance level for our model. This method starts with a given value of the LR-based approach coefficients and tries to update the algorithm's repetitive run until getting the best amount of the LR-based approach coefficients. The best amount happens when it has been possible to maximise the LR-based approach lower bound. The method can be summarised as follows:

Step 1: The upper bound of the first objective is calculated by a heuristic method (UB_1). Then, an initial value is assigned to the LR-based approach coefficient ($\partial_{initiate}$).
Step 2: Solve the problem with Step 1 values to find the lower bound (LB_1) of the problem and decision variable (in the proposed mathematical formulation, we will find x^{p}_{ijh} by running the algorithm in Step 2).
Step 3: Define a sub-gradient factor for the relaxed constraint ($Gamma_{ih}$)

$$Gamma_{ih} = \sum_{j=1}^{pos} \sum_{p=1}^{prod} x^{p}_{ijh} - 1 \quad \forall i \in [1, \dots, op] \ \forall h \in [1, \dots, con] \tag{25}$$

Step 4: Define step size factor (STS) to find the best direction of the algorithm for achieving the best LR based approach coefficient as follows:

$$STS = \frac{\theta(UB_1 - LB_1)}{\sum_{i=1}^{op} \sum_{h=1}^{con} Gamma_{ih}{}^2} \tag{26}$$

It is important to note that θ is a parameter with a value of 2 at step 1. It can be chosen from the decision maker's point of view. Furthermore, its value changed to obtain a better answer in each repetitive run.

Step 5: In each run, the value of ∂_{ih} is updating in Eq. (27). After each run, it will go back to step 2.

$$\partial_{ih} = Max(0, \partial_{ih} + Gamma_{ih} \times STS) \ \forall i \in [1, \dots, op] \ \forall h \in [1, \dots, con] \tag{27}$$

Besides, we consider 50 iterations to stop the algorithm and reach the best value. Figure 5 presents the flowchart of the developed algorithm.

5 Computational study

In this section, the applicability of the LR-based approach is demonstrated in a numerical example. The example is implemented in GAMS 31.2.0 on a laptop with the following configuration: Core i7 and 2.20 GHz processor (ii) 8 GB RAM.

Table 4 Data generation of parameters

Parameter	Value	Parameter	Value
T_{mp}	Uniform (0.75, 1.5)	$TM_{jj'm}$	Uniform (0.2, 0.8)
CAP_{mp}	Uniform (100, 150)	PT_{ijp}	Uniform (1, 6)
$PCAP$	Uniform (300, 400)	PC_{ijp}	Uniform (1, 5)
$VCAP$	Uniform (10, 15)	PR_i	Uniform (1, 5)
DEM_p	Uniform (10, 20)	QC_{ph}	Uniform (2, 5)
$Dist_{pd}$	Uniform (7, 15)	$EL_{i,j}$	Uniform (0.1, 0.2)
EMF	Uniform (0.5, 1)	$EG_{i,j}$	Uniform (0.1, 0.2)
FV	Uniform (0.6, 1)	$l_{i,j}$	Uniform (0.2, 0.5)
$CM_{jj'm}$	Uniform (0.5, 4)	L	Uniform (40, 60)
TP_p	Uniform (0.75, 2)	UR	Uniform (30, 50)
AC_{ph}	Uniform (1, 5)	SL	Uniform (60, 90)

Table 5 Notations used to find the Pareto answers

Notations				
op	*pos*	*prod*	*mac*	*con*
5	5	3	3	3

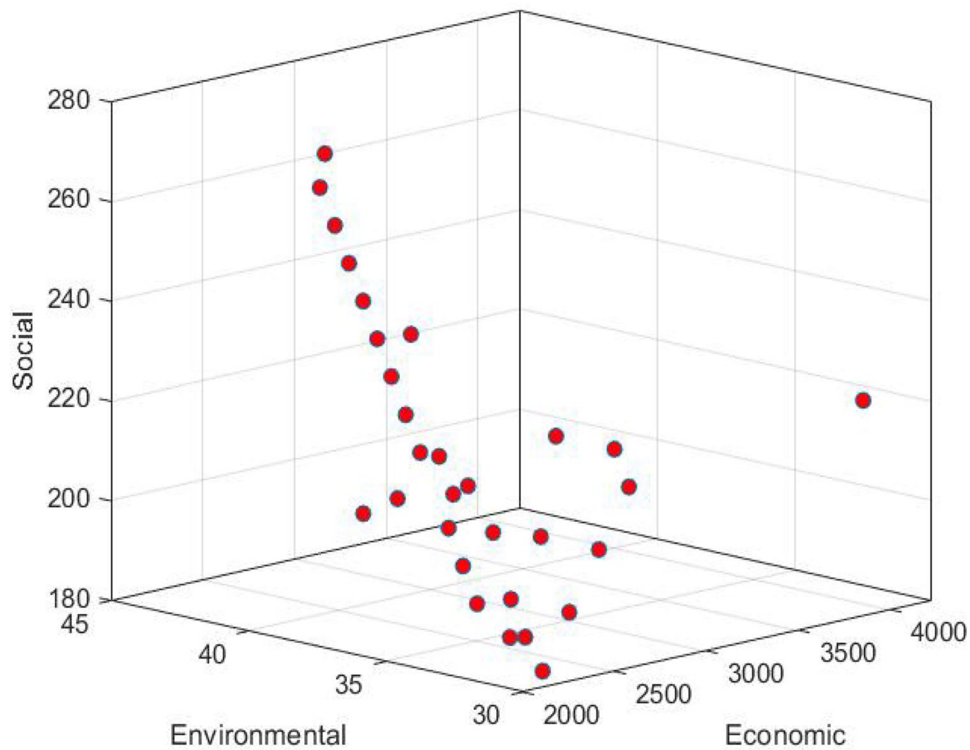
5.1 Computational experiments

Different problem sizes in small, medium, and large sizes have been generated to evaluate the LR-based approach. In the small and medium size of the problem, the LR-based approach results have been compared with the GAMS software. Moreover, it is essential to note that the GAMS software cannot show the results for the large scale of the problem in a logical run time. Therefore, it is essential to compare the gap between the LR-based approach results

Table 6 Pareto answers

Number of answers	Economic sustainability	Environmental sustainability	Social sustainability
1	2309.58	31.34	180
2	2267.23	32.25	186
3	2224.89	33.16	192
4	2251.92	31.59	187
5	2491.92	31.59	190
6	2282.54	34.06	198
7	2309.57	32.5	193
8	2340.20	34.97	204
9	2789.57	32.5	199
10	2607.23	33.4	202
11	2197.85	35.88	210
12	2224.88	37.31	205
13	2347.23	33.4	205
14	2402.54	35.22	210
15	3087.23	33.40	208
16	2455.51	36.78	216
17	2460.19	36.12	216
18	2482.54	35.22	211
19	3144.88	34.31	214
20	2513.16	37.69	222
21	2962.54	35.22	217
22	4229.57	32.5	217
23	2570.81	38.6	228
24	2628.47	39.5	234
25	2713.15	38.84	235
26	2686.12	40.4	240
27	2743.78	41.3	246
28	2801.40	42.2	252
29	2859.09	43.13	258
30	2921.43	43.37	264

Fig. 6 Pareto solutions



with the GAMS software in the small and medium cases to investigate the proposed LR-based approach's efficiency. In this paper, Uniform distribution has been used to generate data to solve the test problem. The values of the parameters are shown in Table 4.

It is essential to note that according to the problem's parameters and solving test problems, the maximum number of iterations of the LR-based approach is 50.

5.2 Pareto solutions

We can find the trade-off between three different objective functions relies on the LP-metrics method. Table 5 shows the data used to obtain Pareto solutions.

Relying on the previous section parameters' data and the above notations, it is possible to find Pareto frontier solutions and payoff tables of the problem to help the decision-maker select an answer between several possible solutions. Table 6 and Fig. 6 depict the Pareto solutions of the problem in 30 different possible answers.

The trade between the answers and the payoff table can be achieved by the Pareto solutions in Table 7, where the bolded values indicate the best amount of each objective function.

According to the results, the best economic sustainability is 2197.85 when the other two objective functions are 35.88 and 210. The best environmental sustainability is 31.34, when the economic sustainability is 2309.58, and the social sustainability is 210. In the end, the best amount of social sustainability is 264, when the others are 2912.43 and 43.37. Therefore, the decision-maker can choose each one of them according to his preference.

5.3 LR-based approach performances

For investigating the applicability of the proposed algorithm, the results of the GAMS software have been compared with the results of LR-based approach in the small and medium scales. The notations of the examples are generated in Table 8 for small, medium, and large scales.

There are two elements to compare the LR-based approach with the GAMS software. The first one is the Gap between the heuristic approach and the exact approach. The second one is the CPU time of the LR-based approach and GAMS software. The results are depicted in Table 9. Moreover, the notation "n/a" means that no

Table 7 Payoff table

Economic sustainability (Z_1)	Environmental sustainability (Z_2)	Social sustainability (Z_3)
2197.85	35.88	210
2309.58	**31.34**	180
2921.43	43.37	**264**

Table 8 Generated examples

Problem number	Scale	Notations					
		op	*pos*	*prod*	*mac*	*con*	Total number of notations
1	Small	2	2	2	2	2	10
2		2	2	2	2	2	10
3		2	2	3	3	2	12
4		3	3	2	2	2	12
5		4	4	2	2	2	14
6		3	3	3	3	3	15
7		5	5	3	2	2	17
8		5	5	3	3	2	18
9	Medium	6	6	3	3	2	20
10		7	7	4	3	3	24
11		8	8	4	3	4	27
12		9	9	4	4	4	30
13		9	9	5	5	5	33
14		10	10	5	5	4	34
15		10	10	5	5	5	35
16		11	11	6	6	5	39
17		12	12	7	7	6	44
18	Large	14	14	7	7	6	48
19		15	15	7	7	7	51
20		15	15	8	8	8	54
21		16	16	8	8	8	56
22		16	16	9	9	9	59
23		17	17	9	9	9	61
24		18	18	10	10	10	66

feasible solutions result from the solving model by GAMS in the allowed time (5000 s).

According to Table 9, the average percentage of the gap between the LR-based approach and GAMS is 0.032524, and the maximum percentage of the gap between results happens in problem number 11 that is 0.089899 when the total number of nodes is 31 as a medium case. Moreover, the minimum percentage of gap between results happens in problem numbers 1, 2, and 3, which is zero because the small case is easier to solve and find the best possible solution for our heuristic method (LR-based approach). These results help us conclude that the LR-based approach has reliable performance because the results of the proposed heuristic method are so close to the exact method, and the gap between them is negligible.

Moreover, the results show a significant advantage in CPU time by using the LR algorithm. The average CPU time by GAMS in the small and medium case is 362.49, while this amount is 9.62 in the heuristic approach. For instance, the gap between them at problem number 2 is 0.2 while this gap is 420.3 in problem number 15. According to Table 9 and Figs. 7 and 8, it is clear that LR has less run time, and the objective functions are approximately similar.

Besides, it is possible to analyse the algorithm's reliability for large-scale problems using statistical hypothesis testing. The values of the objective functions are considered in this manner. The null hypothesis is the equality of the mean of the LR-based approach's objective function with GAMS. On the other hand, the other hypothesis is inequality of them. It is possible to see the results of *P* value in Table 10. Moreover, the confidence level is 95%.

The amount of *P* value is greater than 0.05, so the null hypothesis is acceptable. Therefore, the LR-based approach results are approximately equal to the GAMS results rely on the table. Furthermore, it is possible to implement the LR algorithm for large-scale problems and consider the answers as the optimum amount of real problems.

5.4 Process and production plan

After solving the problem and obtaining Pareto solutions, finding the optimal process plan for each product is possible. According to Table 8, the model's final process plan is generated in Table 11.

Table 9 Results of the generated examples

Problem number	Value of the objective function			CPU time (seconds)	
	GAMS	LR	GAP%	GAMS	LR
1	1761.618	1761.618	0	1.24	1.09
2	3133.192	3133.192	0	1.3	1.1
3	2757.291	2757.291	0	1.45	1.18
4	1858.391	1859.803	0.000759	1.4	1.25
5	1782.82	1788.556	0.003207	1.18	1.1
6	4217.257	4246.896	0.006979	2.49	1.5
7	1912.568	1946.692	0.017529	1.51	1.31
8	2088.7	2109.186	0.009713	1.7	1.6
9	2830.356	2945.179	0.038987	8.31	2.7
10	6202.434	6563.198	0.054968	31.65	9.65
11	10,663.432	11,716.76	0.089899	55.4	21.78
12	10,886.628	11,786.628	0.076358	143.96	27.73
13	20,397.957	21,540.327	0.053034	200.81	30
14	20,581.24	20,815.181	0.053034	190.13	26.81
15	22,451.34	23,324.42	0.037432	450.3	30
16	25,689.771	27,676.202	0.071774	1270	43.78
17	45,549.95	49,566.47	0.081033	3800	85.68
Average	10,868.52618	11,502.21171	0.032524	362.4941176	9.624117647
18	n/a	98,000**	-	5000	190.12
19	n/a	102,000**	-	5000	204.19
20	n/a	160,000**	-	5000	360.46
21	n/a	220,000**	-	5000	654.36
22	n/a	250,000**	-	5000	895.68
23	n/a	400,000**	-	5000	951.23
24	n/a	680,000**	-	5000	1027.6

**The final value has been rounded in the large cases

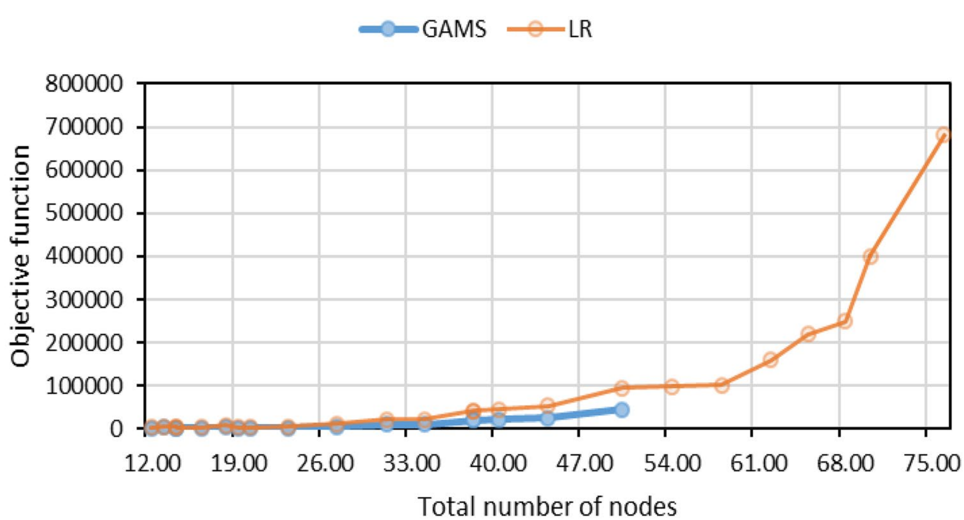


Fig. 7 Changes of objective functions according to the total number of nodes

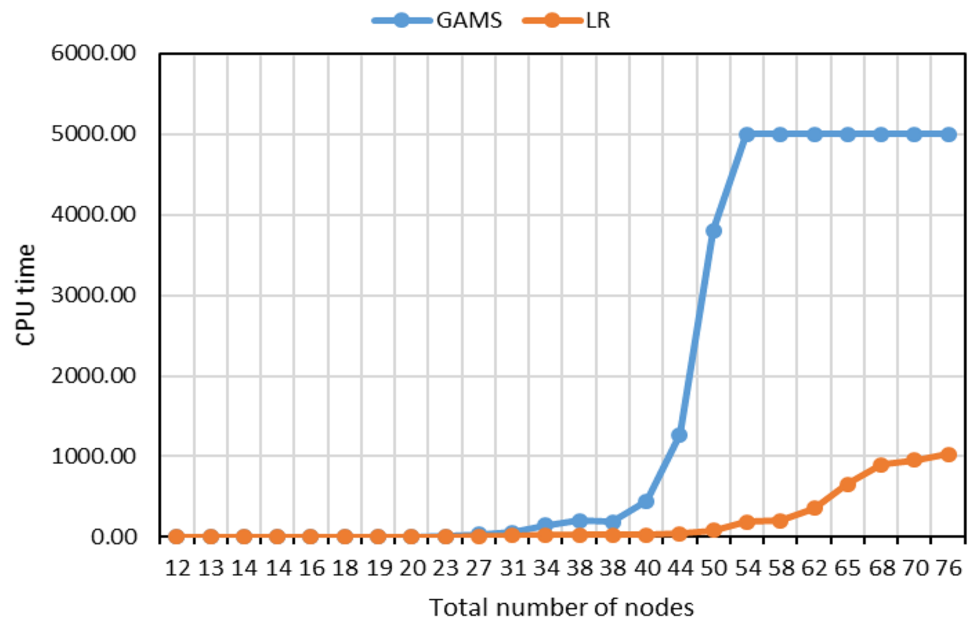


Fig. 8 Changes of CPU time according to the total number of nodes

Table 10 Results of the statistical hypothesis testing in small and medium scale

Element	***P* value**
Objective function	0.58

Table 12 Changes of DEM_p

$\mathrm{DEM_p}$	**Lp-metrics**
5	0.098
10	0.092
15	0.087
20	0.083
25	0.079
30	0.076
35	0.073
40	0.070
45	0.067
50	0.065
55	0.063
60	0.061
65	0.059

Furthermore, in the proposed process plan, the system wants to answer market demands and produce three different products P1, P2, and P3. Moreover, product P1, product P2, and product P3 have the same number of operations (five operations). However, operations of product P1 are different from operations of product P2 and product P3 as well. To discuss more in detail about reconfigurability of the system, as illustrated in Table 11, for product P2 the first operation $\mathrm{Op_2 1}$ will be performed on machine M2 using configuration H1, afterwards, to perform the following operation $\mathrm{Op_2 3}$ on the machine M2, the system will be reconfigured using configuration H2. The differences of the operations are due to the used machines and configurations.

Table 11 Optimal process plan

P1	Operations	$\mathrm{Op_1 1}$	$\mathrm{Op_1 2}$	$\mathrm{Op_1 3}$	$\mathrm{Op_1 5}$	$\mathrm{Op_1 4}$
	Machines	M2	M2	M2	M3	M3
	Configuration	H1	H1	H1	H3	H3
P2	Operations	$\mathrm{Op_1 1}$	$\mathrm{Op_1 2}$	$\mathrm{Op_1 3}$	$\mathrm{Op_1 5}$	$\mathrm{Op_1 4}$
	Machines	M2	M2	M3	M3	M1
	Configuration	H1	H2	H2	H2	H2
P3	Operations	$\mathrm{Op_1 1}$	$\mathrm{Op_1 2}$	$\mathrm{Op_1 3}$	$\mathrm{Op_1 5}$	$\mathrm{Op_1 4}$
	Machines	M3	M3	M1	M1	M1
	Configuration	H2	H2	H3	H3	H3

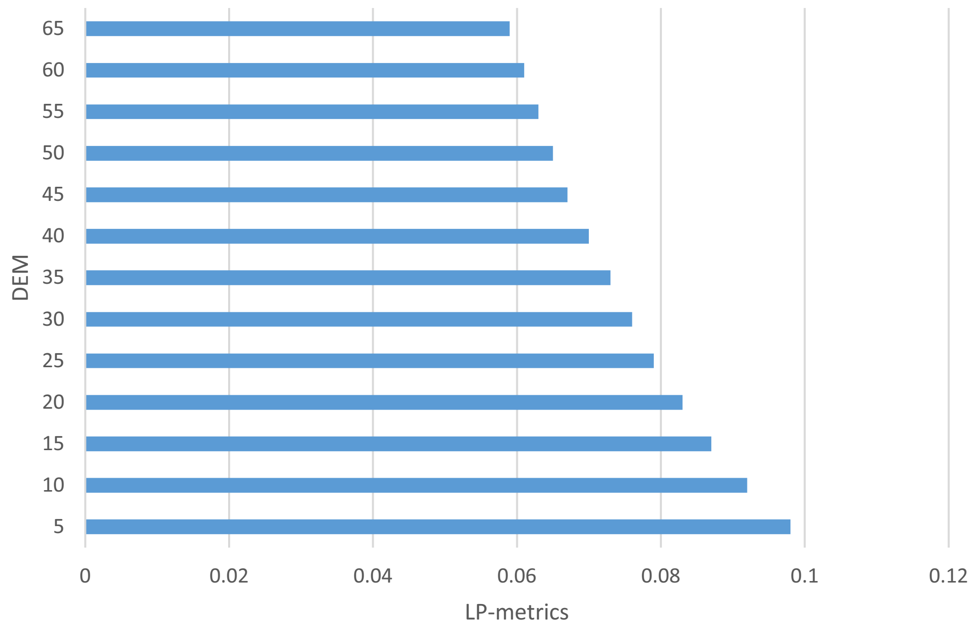


Fig. 9 Changes of DEM_p

Table 13 Results of changing the weights

Weight 1	Weight 2	Weight 3	**LP-metrics**
0.8	0.1	0.1	0.092
0.2	0.3	0.5	0.451
0.2	0.4	0.4	0.361
0.3	0.5	0.2	0.181
0.3	0.3	0.4	0.391
0.4	0.3	0.3	0.271
0.5	0.3	0.2	0.195
0.5	0.2	0.3	0.215
0.6	0.2	0.2	0.124

For the production planning part, the optimum quantity of production of each product has been discovered. For instance, for the example mentioned above, the optimum quantity of P1 is 10, P2 is 15, and P3 is 20.

6 Sensitivity analyses and discussions

By analysing the sensitivity of various parameters on the developed model, it is possible to find the effects of each one of them separately. This sensitivity analysis can affect different parts of the model as follows:

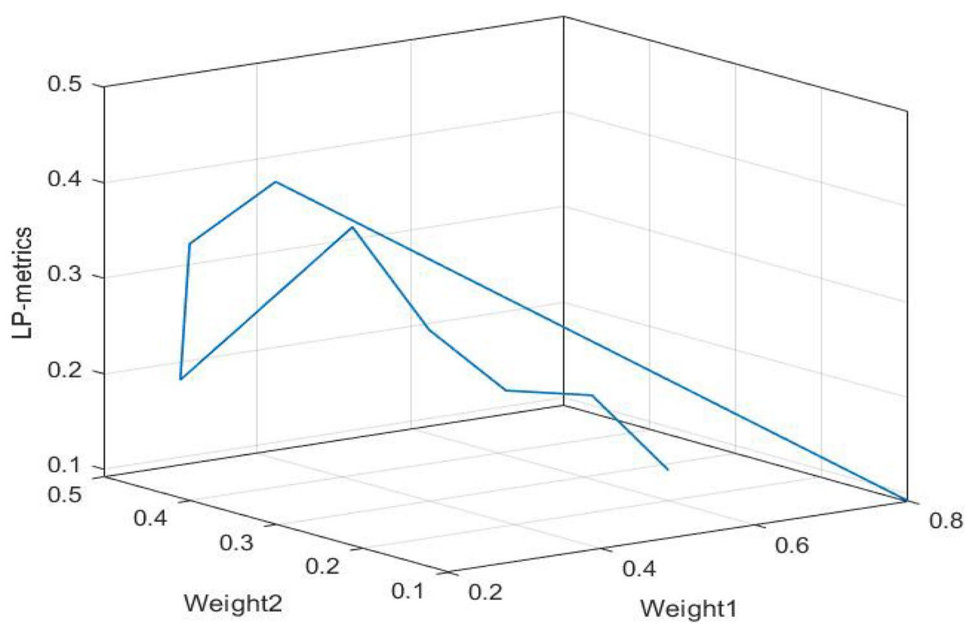


Fig. 10 Comparison of weight 1 and weight 2

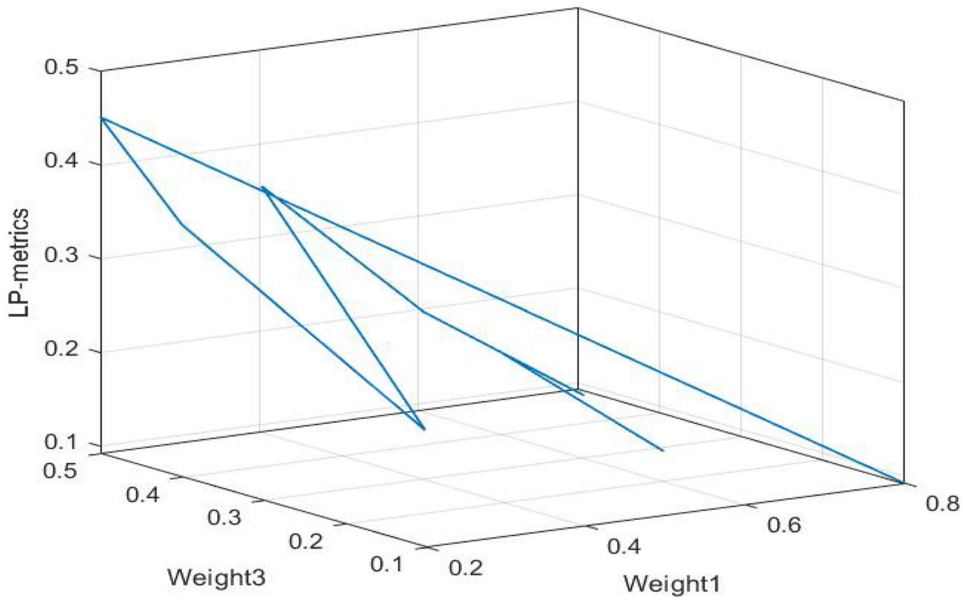


Fig. 11 Comparison of weight 1 and weight 3

6.1 Changes of DEM_p

According to Table 12 and Fig. 9, it can be inferred that the more increase in the amount of the demand, the more reduction in the final value of the Lp-metrics-based approach can be seen. These changes depict the validity of the proposed model. Because in the real world, when demand increases, a system can have better performances from before when there is no shortage. In the proposed model for the RMS, the shortage is not considered; the value of the objective is getting better by the increases of demand, so the model is valid.

6.2 Changes of weight_1, weight_2, and weight_3

The changes of the weights can have a significant impact on the LP-metrics-based approach objective function. Therefore, a reasonable chance of them discovering the value of the LP-metrics-based approach and plotting them in a three-dimensional graph can show the problem's sensitivity to them better than the other ways. Table 13 with Figs. 10, 11 and 12 show the results of changing the weights on the problem.

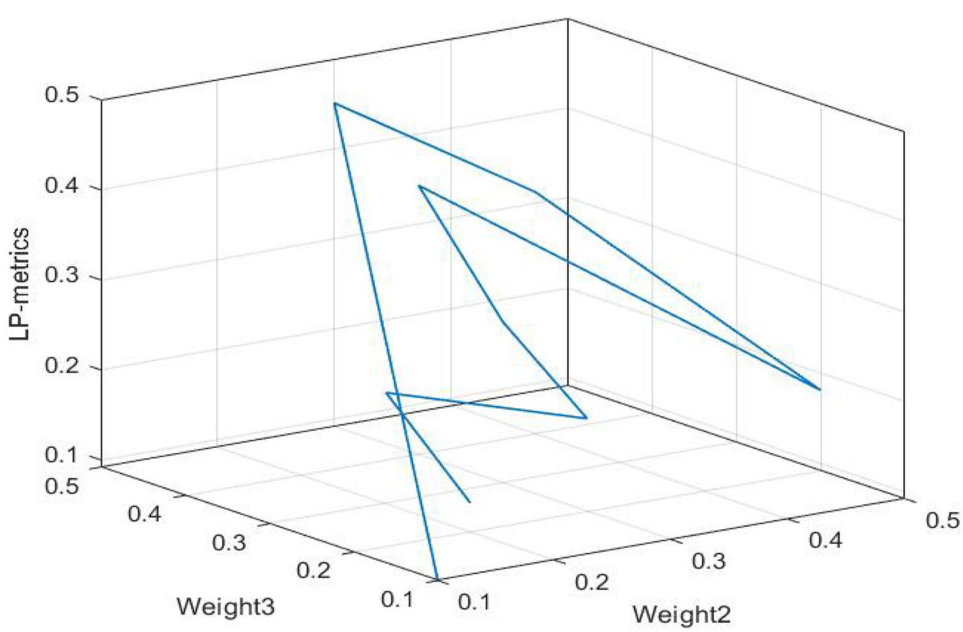


Fig. 12 Comparison of weight 2 and weight 3

Although in most cases of todays' world problem, the cost function and economic issues are the most critical part of the world, our problem shows great respect to the environmental and social sustainability manners. The weight of economic sustainability has the most critical impact on the LP-metrics-based approach objective function, but the differences between this impact and other objective impacts are not significant.

6.3 Discussions

It is important to note that one of the most critical process planning roles is to reduce the total cost of process machining. Besides, optimising this kind of problem and compare the results of an algorithm with another type of method is vital. Rely on these points of view; it is possible to use an algorithm with good performance and prove the application of the proposed model [58]. In this paper, the GAMS solver is used to show the application of the proposed model. We were able to find the optimum solutions of the objective functions, process planning, and production planning in the several examples. The GAMS solver is not able to solve the proposed model on a large scale. Therefore, to show the appliance of the model on large scales and find the values close to the optimal solutions, we implemented LR based approach. The implemented approach was reliable for the proposed model, and it performed well. Besides, the logical behaviour of the proposed model is presented by changes in the parameters.

We presented several options for the managers and decision-makers to select between various sustainability factors. The manager can choose the different weights for each aspect of sustainability and decide more widely according to the solving procedure and results. For example, in some countries, the most critical aspect of sustainability is to respect the environment. Therefore, they can choose the maximum possible weight of environmental sustainability relying on other constraints in the real world. In some other countries, the costs are the only and important limitation of the production. Therefore, they can focus on the economic sustainability of the proposed problem. Besides, we presented the behaviour of the problem on a large scale, which helps the decision-maker have a better view of the consequences of a decision and its effects on other aspects of people's lives.

7 Conclusions and future works directions

In this paper, the whole elements of sustainability like social, environmental, and economic are combined with the process and production planning in a reconfigurable manufacturing environment. The sustainability indicators include the harmful liquids and gases emission during the production and its effects on the operator's body and the social manners of operators and people in the neighbourhood. The work is aimed to minimise economic and environmental sustainability and tried to maximise social sustainability. Hence, the addressed problem is modeled in a multi-objective point of view and solved by the Lp-metric and LR-based approach heuristic algorithm. Therefore, the main contribution can be named as implementing all aspects of sustainability in an RMS environment and discovering the best production quantity and process sequences rely on the innovations.

Forward future work directions, metaheuristic such as NSGA-II, AMOSA, WGA, etc., implementations and comparisons with both results, are expected. Moreover, the integration of production planning and scheduling can be addressed. Finally, different production and process planning concepts for multiple contexts can be considered, such as dynamic, stochastic, and smart manufacturing.

Author contribution All the authors have involved equally in the realized work. Mr. M.A. Yazdani, A.H. Khezri, L. Benyoucef: paper writing, problem formulation, approaches proposal and experimental performing and analysis.

Availability of data and materials The used data and materials are available when requested.

Declarations

Ethical approval The submitted work is original and has never been published elsewhere in any form or language.

Consent to participate Not applicable.

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Conflict of interest The authors declare no competing interests.

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