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Abstract: This research examines the integration of workforce and process planning in reconfigurable manufacturing environment, focusing on sustainability's economic, social, and environmental dimensions. It evaluates social sustainability through new indicators, including flexible working hours and workforce hazard risks. A new mixed-integer linear programming model is proposed to minimize costs, social sustainability metric, production time, and hazardous waste. The model's effectiveness is assessed with RMS benchmarks using the augmented weighted Tchebycheff method for multi-objective optimization and data envelopment analysis to rank solutions, providing a detailed evaluation of RMS configurations.

Keywords: Reconfigurable manufacturing system, Multi-objective optimization, Workforce planning, Process planning, Sustainability, Augmented weighted Tchebycheff

1. INTRODUCTION

The reconfigurable manufacturing system (RMS) plays a pivotal role in enhancing production flexibility, reducing waste, and increasing overall efficiency, contributing to a more eco-friendly and ethical manufacturing landscape. Achieving this involves leveraging modular machinery, adaptable workflows, and a skilled workforce. Efficient job scheduling and workforce planning are key to optimizing RMS operations. Job scheduling coordinates various manufacturing activities, such as production runs, maintenance, and idle times, by considering factors like satisfying demand and resource availability to devise a plan that minimizes waste and maximizes productivity. The concept of flexibility inherent in RMS facilitates swift adjustments to shifts in demand. Meanwhile, workforce planning focuses on determining the necessary workforce size and skill set to meet the demands of the job schedule. Within RMS, this aspect of workforce planning is crucial for swiftly reconfiguring staff assignments in light of changes in the manufacturing environment.

A sustainable reconfigurable manufacturing system (SRMS) is designed to be versatile and capable of adjusting to variations in product demand and manufacturing requirements. Additionally, SRMS focuses on minimizing its environmental footprint while enhancing its societal and economic benefits. The social dimension of SRMS considers the impact on individuals, including workers, the local community, and broader society. This includes crucial social elements such as 1) employee health and safety, 2) job satisfaction and engagement, 3) effects on the local community, and 4) commitment to social responsibility along with promoting diversity, equity, and inclusion. By addressing these social factors in the development and execution of RMS, businesses can foster a more sustainable and ethical manufacturing environment that serves the interests of both the organization and the community. This approach not only strengthens the company's reputation but also helps in attracting customers, investors, and shareholders.

In the realm of RMS, scholars have explored the integration of sustainability dimensions. Khezri et al. (2021)introduced a multi-objective framework for process planning within RMS that emphasizes minimizing costs, makespan, gas emissions, and hazardous liquid waste. Meanwhile, study Khettabi et al. (2022) implemented two metaheuristic strategies alongside a subsequent approach for multi-objective process planning in Sustainable RMS (SRMS), aiming to reduce overall costs, completion times, and gas emissions. In another contribution, Ostovari et al. (2023) showcased a mixed integer linear multi-objective robust programming approach tailored for selecting the optimal reconfigurable manufacturing tools (RMTs), with a focus on total costs and energy usage. Additionally, Vahedi-Nouri et al. (2022) explored a constraint programming method for workforce planning and job sequencing within RMS, specifically accounting for the risk of workforce accidents amidst the COVID-19 pandemic.

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This research examines the integration of workforce and process planning (WPP) in SRMS. Furthermore, we not only analyze the overall cost, which encompasses both operational and workforce expenses, and the total time to completion of operations, but we also prioritize human-centric social considerations by emphasizing workforce safety and flexible working hours, alongside the environmental impact of hazardous liquids. We simultaneously account for the capability of machines to execute specific operations and the proficiency of the workforce to undertake these tasks. The structure of the paper is organized as follows: The next section delineates the problem and its mathematical model. The third section outlines the methodologies employed for addressing multi-objectivity and ranking solutions on the Pareto front. The fourth section details the computational results achieved. The paper concludes with the final section that offers information on future research directions.

2. PROBLEM DESCRIPTION AND FORMULATION

2.1 Problem description

In a scenario where a single-unit product is being manufactured within an RMS, a sequence of operations is crucial for achieving the final product. These operations are interlinked through precedence constraints, ensuring a logical flow of manufacturing processes as illustrated in Fig. 1. Each operation is characterized by a specific set of tools, each capable of performing the operation, along with the necessary tool approach directions (TADs), which include orientations such as x, y, and z. Machines within this environment are defined by their respective sets of available configurations and compatible tools. A particular configuration is identified by its associated TADs, aligning with the requirements of the operations to be performed. Consequently, the execution of an operation necessitates a specific combination of machine, configuration, and tool, collectively referred to as a triplet and denoted by (M, C, T). The compilation of these triplets forms what is known as process plan generation, delineating the detailed workflow for manufacturing the product. In addition, machines can be operated by a group of skilled workerforces.

The workforce is assumed to be heterogeneous, implying that each worker possesses identical skill sets, enabling them to operate the machinery effectively. The structure of the workforce, along with the process plan, is methodically laid out in a matrix format, encompassing n columns that signify the total number of operations to be performed. This matrix is organized into five distinct rows that categorize the operation, machine, configuration, tool, and workforce, respectively. A specific example of such a process plan is illustrated in table 1, where the positioning of $OP2$ in the third column suggests its execution as the third position within the proposed WPP. This operation, scheduled to follow its predecessor $OP3$, will utilize Machine $M1$ configured to $C1$ and employ Tool $T4$. To process this operation, workforce $L3$ is allocated, underscoring the collaborative integration of machine eligibility and workforce capability in realizing the process plan.

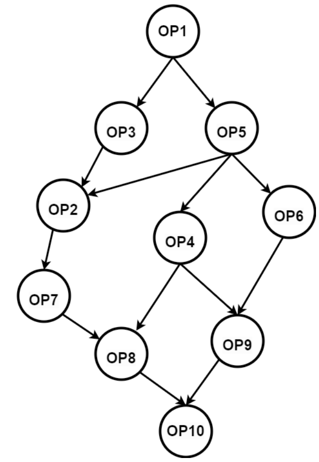

Fig. 1. Operation precedence graph.

This study considers two classical objective functions in the production scheduling problem, namely makespan and overall cost. The operating cost, the machine and triplet-changing cost, and the assignment cost of the workforce to the system are what determine the overall cost. Makespan is directly correlated with the total time required for the completion of all operations on the machines, including the availability of time for the assigned workforce, processing time, and reconfiguration time of triplets. Moreover, the paper considers social sustainability metric and hazardous liquid waste. The sustainability metric states workplace risk hazards and flexible work hours. Workplace risk hazards concern the workforce susceptibility score. Furthermore, in the flexible work hours aspect, the worker determines his or her entrance preference to be available in the system. Waste water or oil, production waste, and surface treatment waste are all included in the group of hazardous liquid wastes. Some assumptions for this problem are developed based on practical scenarios, as follows:

- The susceptibility score of the workforce is calculated based on their accumulated training hours and overall experience, serving as a measure of their adaptability and efficiency.
- In flexible work hours, a preference matrix is utilized to schedule work hours, where earlier arrival times are more favored.
- One workforce has to be assigned to the system within entrance time.
- The time needed to complete operations is fixed and dictated by the specific combination of machine, configuration, and tool utilized, ensuring predictable and unchanging processing times.
- Each operation is guaranteed to be executable by at least one combination of machine, configuration, and tool, with each machine configuration being versatile enough to support multiple operations.
- Reconfigurable manufacturing tools offer the flexibility to modify their performance and speed through adjustments in their setup. The duration required to reconfigure a machine is influenced by the transition from one configuration to another.

2.2 Mathematical formulation

The model is formulated in this manner:

Table 1. Illustrative instance of workforce and process planning.

Operation	OP1	OP3	OP2	OP7	OP5	OP4	OP6	OP8	OP9	OP10
Machine	M3	M2	M1	M3	M5	M1	M3	M5	M5	M2
Configuration	C3	C2	C1	C3	C1	C2	C3	C2	C2	C2
Tool	T1	T4	T4	T2	T5	T5	T1	T1	T1	T3
Workforce	L2	L1	L3	L2	L4	L3	L2	L4	L4	L1

Indices

$i, i' \in I$	Index of operation.
$m, m' \in M$	Index of machine.
$p \in P$	Index of position.
$l \in L$	Index of workforce.
$tr, tr' \in TR$	Index of triplet.
$t \in T$	Index of time.

Parameters

tp_{imtr}	Processing time of operation i performed on machine m with triplet tr.
$cmt_{trtr'}$	Triplet changing time from triplet tr to triplet tr'.
$ctt_{mm'}$	Machine changing time from m to machine m'.
ta_t	Starting time t.
RL_l	Workforce l susceptibility score.
lP_{lt}	Workforce priority to entry at time t.
$Pred(i, i')$	1 if operation i needs to be processed before i'.
$costl_l$	Assignment cost of workforce l to the system.
$costa_{imtr}$	processing cost of operation i in machine m with triplet tr.
$costm_{mm'}$	Machine changeover cost.
$costr_{trtr'}$	Triplet changeover cost.
l_{itr}	Required liquid for operation i with triplet t.
EP_{itr}	Estimated hazardous liquid waste for operation i when using triplet tr.
L	Total available liquid.
wc_{imtr}	1 if machine m with triplet tr is eligible to perform operation i.
aw_{lm}	1 if workforce l is capable to work with machine m.

Variables

x_{ipmtr}	1 if operation i is being processed at position p by machine m with triplet tr, and 0 otherwise.
y_{lt}	1 if workforce l assigned to system at the entrance time t, and 0 otherwise.
$tc_{ptr}^{tr'}$	1 if between position $p-1$ and p there has been a change between triplet tr and tr', and 0 otherwise.
$mc_{pm}^{m'}$	1 if between position $p-1$ and p there has been a change between machine m and m', and 0 otherwise.

$$\min f1 = \sum_{i,p,m,tr} x_{ipmtr} \times costa_{imtr} + \sum_{l,t} y_{lt} \times costl_l + \sum_{p,m,m'} mc_{pm}^{m'} \times costm_{mm'} + \sum_{p,tr,tr'} tc_{p,tr}^{tr'} \times costr_{trtr'} \tag{1}$$

$$\min f2 = \frac{\alpha_1}{\max_l RL_l} \sum_{l,t} y_{lt} \times RL_l + \frac{\alpha_2}{\max_{l,t} lp_{lt}} \sum_{l,t} y_{lt} \times lp_{lt} \tag{2}$$

$$\min f3 = \sum_{l,t} y_{lt} \times ta_t + \sum_{i,p,m,tr} x_{ipmtr} \times tp_{imtr} + \sum_{m,m'} ctt_{mm'} \times mc_{pm}^{m'} + \sum_{tr,tr'} cmt_{trtr'} \times tc_{p,tr}^{tr'} \tag{3}$$

$$\min f4 = \sum_{i,p,m,tr} x_{ipmtr} \times l_{itr} \times EP_{itr} \tag{4}$$

$$\sum_{i,m,tr} x_{ipmtr} = 1 \quad \forall p \tag{5}$$

$$\sum_{p,m,tr} x_{ipmtr} = 1 \quad \forall i \tag{6}$$

$$\sum_{i,tr} x_{ipmtr} + x_{ip-1m'tr} \leq mc_{pm}^{m'} + 1 \quad \forall p \geq 2, m, m' \tag{7}$$

$$\sum_{i,m} x_{ipmtr} + x_{ip-1mtr'} \leq tc_{p,tr}^{tr'} + 1 \quad \forall p \geq 2, tr, tr' \tag{8}$$

$$\sum_{p,m,tr} p \times x_{ipmtr} \leq \sum_{p,m,tr} p \times x_{i'pmtr} \quad \forall i, i' \in Pred(i, i') \tag{9}$$

$$\sum_{t,t'} \sum_{t,t'} tc_{p,tr}^{tr'} = 1 \quad \forall p \tag{10}$$

$$\sum_{l,t} y_{lt} \leq 1 \tag{11}$$

$$\sum_{i,tr,p} x_{ipmtr} \leq \sum_{l,t} y_{lt} \quad \forall m \tag{12}$$

$$\sum_{i,p,m,tr} x_{ipmtr} \times l_{itr} \leq L \tag{13}$$

$$\sum_{p} x_{ipmtr} \leq wc_{imtr} \quad \forall i, m, tr \tag{14}$$

$$\sum_{i,p,tr} x_{ipmtr} \leq \sum_{t} aw_{lm} \times y_{lt} \quad \forall l, m \tag{15}$$

The first objective function, as detailed in (1), focuses on minimizing overall costs. This includes the expenses associated with assigning the workforce, the costs incurred from processing operations, as well as the expenses arising from machine and triplet changing. The second objective function, outlined in (2), is aimed at optimizing a social sustainability metric. This metric takes into consideration the risks associated with workforce hazards and the implementation of flexible working hours. It's important to note that to account for the disparate scales of these terms, normalization is applied by dividing each term by its maximum observed value. The third objective function, presented in (3), targets minimizing the total production time, incorporating the entrance time of the workforce, processing time of operations, and times required for changing machines and triplets. Equation (4) states the amount of hazardous liquid waste.

Constraints (5) and (6) mandate that each position in the process plan must host only one operation, and every operation is to be executed exactly once, respectively. Constraints (7) and (8) address the necessity of machine changes and adjustments in triplets between consecutive positions, $p-1$ and p, respectively. Constraint (9) ensures precedence relations between operations are respected. Constraint (10) limits the system to allow just a single change between triplets across adjacent positions. Constraint (11) specifies that only one workforce available at a given time may be assigned to the system. Constraint (12) stipulates that operations can only proceed on machines to which a workforce has been allocated within the system. Constraint (13) outlines the maximum capacity for liquid handling within the production system. Constraint (14) details the compatibility requirements for executing processing operations on specific machines and triplets. Lastly, (15) specifies that only the workforce possessing the necessary skills to operate all machines mentioned in the process plan is capable of assignment to the system.

3. SOLUTION APPROACH

To create optimal process plans, an AWT method has been formulated. This method aims to identify the most favorable balance among four critical objectives: overall production cost, sustainability metric, makespan, and hazardous liquid waste. Subsequently, the optimal solution is chosen from the generated Pareto solutions through the application of DEA.

3.1 Adapting the augmented weighted Tchebycheff method for multi objective optimization

Given the diverse aspects of sustainable development encompassed by the proposed model, which is framed as a multi-objective mathematical programming mode, employing a suitable method for solving the four-objective model is essential. The augmented weighted Tchebycheff (AWT) method, known for its applicability and straightforwardness, is chosen for addressing this multi-objective problem. This approach facilitates the effective resolution of the model's objectives, aligning with the principles of sustainable development. The foundational application of the Tchebycheff numerical method within the realm of multi-objective mathematical programming models traces back to the work by Bowman Jr (1976), which utilized this technique for solving complex multi-objective problems. Building on this foundational concept, Steuer and Choo (1983) introduced the concepts of augmented weighted programming and Augmented Weighted Tchebycheff lexicographic models. A key advantage of the Tchebycheff method lies in its effectiveness across both continuous and discrete decision-making scenarios, as evidenced by its robust performance. Further exploration and application of this method in research, such as that conducted by Razmi and Maghool (2010); Yousefi-Babadi et al. (2023), underscore its utility and effectiveness in addressing intricate optimization challenges.

Defining the ensemble of objective functions by $m \in M$ and assigning parameters such as f_m for the value of the objective function, f_m^* for its optimal value, alongside f_m^{Max} and f_m^{Min} to denote the function's maximum and minimum values, respectively. Additionally, λ_m represents the weighting coefficients for the objective functions. With the augmentation factor ω set within the interval $[10^{-3}, 10^{-1}]$, the linearized framework of the AWT method can be articulated as (16):

$$\min\{\phi - \omega \sum_m \frac{f_m - f_m^*}{f_m^{Max} - f_m^{Min}}\} \tag{16}$$

$$\lambda_m \frac{f_m - f_m^*}{f_m^{Max} - f_m^{Min}} \leq \phi$$

$$\sum_m \lambda_m = 1, \lambda_m \geq 0$$

3.2 Data envelopment analysis

DEA stands out as a crucial decision-making approach that deals with multiple inputs and outputs. This technique is employed to identify the optimal decision-making unit (DMU) across various domains. DEA enables each DMU to establish its own weights for inputs and outputs, positioning it in the most advantageous light compared to others. The model under consideration assesses the efficiency of n DMUs, indexed by $j = 1$ to s. It characterizes each DMU by its inputs, $x_{1j}, x_{2j}, \ldots, x_{mj}$, and outputs, $y_{1j}, y_{2j}, \ldots, y_{ij}$. This investigation utilizes the methodology developed by Charnes et al. (1978), a detailed discussion of which will follow as (17).

$$\min \theta \tag{17}$$

$$\theta X_{ip} \geq \sum_{j=1}^{n} w_j x_{ij} \quad \forall i$$

$$y_{rp} \leq \sum_{j=1}^{n} w_j y_{rj} \quad \forall r$$

$$w_j \geq 0 \quad \forall j$$

w_s is a dual variable, and θ is the overall score of the unit p. The proposed mathematical model has four objective functions. The mathematical model in question is formulated with four objectives aimed at minimization. Within this context, objectives z_1 and z_3 are treated as input variables, while objectives z_2 and z_4 are designated as the output variables in the DEA model.

4. COMPUTATIONAL RESULTS

This segment evaluates the proposed models' effectiveness in addressing WPP challenges within RMS, leveraging established benchmarks in the field. The parameter details are outlined in table 2, drawing from the studies by Yazdani et al. (2022); Ostovari et al. (2024). Specifically, table 1 serves as a benchmark example, illustrating a process plan comprising a sequence of operations

$\{OP_1, ..., OP_{10}\}$. This plan is supported by ten reconfigurable machines, denoted as $\{M_1, ..., M_{10}\}$, which are equipped with five uniform configurations $\{C_1, ..., C_5\}$ and a variety of five tools $\{t_1, ..., t_5\}$. It is imperative that the sequence of operations adhere to a predefined precedence graph, as depicted in Fig 1. Additionally, the operation of machines is facilitated by a workforce comprising ten skilled individuals $\{L_1, ..., L_{10}\}$, who are available across three distinct time slots $\{T_1, ..., T_3\}$. The eligibility rate for operations is set at 70%, indicating that each operation can be performed with 70% of the available machine and triplet combinations. Similarly, the capability rate for the workforce is determined to be 90%, signifying that each machine can be operated by 90% of the available workforce. The benchmark is executed using GAMS 25.1 on a PC equipped with a Core i7 processor, running at 2.5 GHz, and supported by 32 GB of RAM.

To identify exemplary efficient solutions from the Pareto frontier, a set of 19 diverse weight vectors is created, with each λ_m being non-negative and the sum of all λ_m equaling 1. These weight vectors are subsequently applied within the augmented weighted Tchebycheff approach, as outlined in Equation 16, to derive sample-efficient solutions along the Pareto front. The procedure involves solving the problem 19 times, each instance utilizing a distinct weight vector, to procure 19 representative efficient solutions from the Pareto frontier. The outcomes of these solutions are detailed in table 3. In the modified approach, normalized objective functions are employed; however, the values of the objective functions are reverted to their original scales when displayed in table 3. This adjustment ensures clarity and avoids potential confusion for the reader.

Given the results provided, decision-makers are equipped with multiple options for selecting the ideal solution. It's crucial to simultaneously take into account the values across all objective functions. For instance, in DMU 10, the comprehensive analysis reveals a total cost equals 57.59 Related Money Units (RMU), a sustainability metric is 0.59, a makespan equals 536.5 minutes, and a hazardous liquid volume is 0.39 Hazardous Units (HU).
Fig. 2 illustrates the objective function values of Pareto solutions in groups of three. This visualization leads to the understanding that the outcomes of varying objective functions are not necessarily consistent, indicating that each objective function should be evaluated separately. Specifically, Fig. 2a presents a scatter plot for the three objective functions: cost, makespan, and sustainability metric; Fig. 2b displays a scatter plot for cost, sustainability metric, and hazardous liquid; Fig. 2c reveals a scatter plot for sustainability metric, makespan, and hazardous liquid; and Fig. 2d showcases a scatter plot for cost, makespan, and hazardous liquid.

Table 3 reveals that the AWT method has identified 19 Pareto solutions. Consequently, the CCR input-oriented model is utilized to select the optimal solution from the Pareto solutions derived via the AWT method. In this approach, the results are regarded as DMUs, and the objective functions are classified as inputs or outputs depending on their characteristics. Referring to table 3, DMUs 4, 8, and 19 emerge as the most efficient WPP.

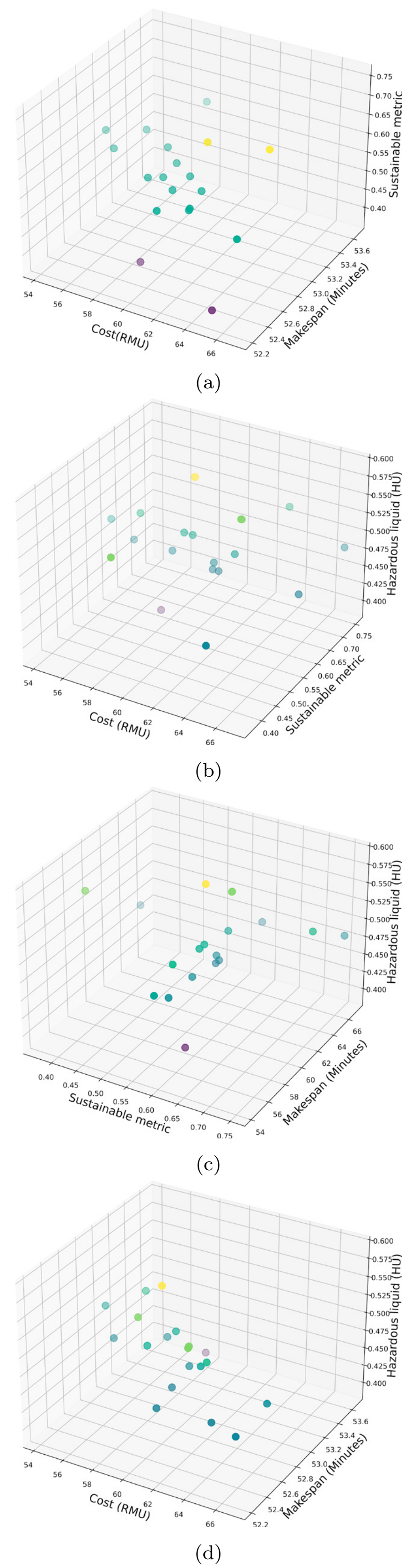

Fig. 2. Pareto optimal solutions obtained by optimization algorithm

Table 2. List of parameters.

Parameter	Value	Parameter	Value
tp_{imtr}	Uniform (1,6)	$costa_{imtr}$	Uniform (2,5)
$ctt_{mm'}$	Uniform (0.5,1.5)	EP_{itr}	Uniform (0.1,0.2)
$cmt_{trtr'}$	Uniform (1.5,2)	l_{itr}	Uniform (0.2,0.5)
$costr_{trtr'}$	Uniform (0.4,1.2)	L	Uniform (40,60)
$costm_{mm'}$	Uniform (0.5,4)	RL_l	Uniform (0.0001,0.005)
$costl_l$	Uniform (10,15)	ta_t	[480,540,600]

Table 3. Efficient solutions from the Pareto frontier

DMU	Cost	Sustainable metric	Makespan	Hazardous liquid	Efficiency	Rank
1	61.49	0.59	522.6	0.47	0.891	13
2	62.93	0.59	523.9	0.55	0.914	9
3	63.42	0.74	525.1	0.52	0.872	15
4	59.92	0.59	526.4	0.59	1	1
5	59.2	0.59	525.8	0.51	0.928	7
6	61.1	0.59	525.3	0.47	0.90	12
7	62.55	0.59	526.1	0.5	0.88	14
8	54.22	0.59	529.8	0.5	1	1
9	66.71	0.59	522.2	0.47	0.832	16
10	57.59	0.59	536.5	0.39	0.964	5
11	66.92	0.75	525.8	0.48	0.804	17
12	58.4	0.59	529.9	0.48	0.942	6
13	62.98	0.59	523.7	0.55	0.913	10
14	61.18	0.59	527.3	0.48	0.903	11
15	55.78	0.59	528	0.48	0.974	4
16	59.77	0.59	528.3	0.51	0.922	8
17	64.86	0.37	522.9	0.47	0.995	2
18	56.25	0.59	531.2	0.52	0.989	3
19	58.84	0.37	525.4	0.55	1	1

5. CONCLUSION AND PERSPECTIVES

In this paper, we have introduced a unified approach for integrating sustainable WPP within the framework of RMS. Despite the growing fascination with mathematically modeling sustainable RMS, holistic methodologies that fully embrace the tripartite pillars of sustainability—namely, economic, environmental, and social factors—are still exceedingly uncommon. Our methodology synergies sustainability considerations with decisions related to WPP specific to sustainable RMS environments. Through the application of mathematical programming, we have integrated assessments of environmental, economic, and social impacts. A multi-objective mixed-integer linear programming model was developed for this purpose. Moreover, we tackled a renowned benchmark in RMS scenarios using a modified version of the AWT method. Our analysis demonstrates how Pareto optimal solutions can assist decision-makers in choosing WPP that closely match their objectives and preferences across environmental, economic, and social dimensions. Additionally, we employed a DEA approach to ascertain the ranking of various solutions. Future research directions could involve addressing uncertainties in related parameters and crafting meta-heuristic algorithms tailored to the problem's specifics. Moreover, explore simulation-based optimization techniques to depict more accurate scenarios relevant to SRMS.

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