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Improved Sustainability in Cellular Manufacturing Systems: Sensitivity Analysis of A Penalty Function Driven NSGA-II

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Abstract:

Purpose: Research suggests that material handling costs account for 20-50% of production costs. Furthermore, these production cost could be reduced by 10-30% by dynamically changing the layout. We propose an integer programming model to sustainably solve plant layouts in a financially conservative, yet environmentally friendly way.

Design/methodology/approach: We propose a bi-objective Non-dominated Sorting Genetic Algorithm (NSGA-II) approach to optimizing Dynamic Cellular Manufacturing Systems (DCMS). The mathematical model's first objective function minimizes economic cost, while the second objective function minimizes environmental emissions. The NSGA-II solver uses the penalty approach to handle constraints. The solver is customized beyond the traditional NSGA-II, such that constraint violating solutions are repaired, and unique solutions are prioritized to enhance population diversity and exploration.

Findings: Although a manufacturing plant layout may be optimal for a particular demand period, when the demand changes that system may not be optimal for the new demand period. Extensive simulation shows that our bi-objective model dominates the single objective model from literature. Adding an environmental second objective to DCMS reveals that the most economical solution is often the least environmentally friendly approach, and vice versa. A convex relationship is observed between the two objectives. A weighted compromise is required when setting up a sustainable production system.

Research limitations/implications: Only carbon emissions were simulated. Hazardous liquid waste, Energy consumption, and water consumption were not considered.

Practical implications: Manufactures and their contracted line builders will need to consider environmental implications when setting up a production line. Decision makers need to be aware that the most cost conservative approach may lead to significantly higher carbon emissions.

Social implications: The social pillar of sustainability was incorporated via a set of constraints in the mathematical model of this study. The solution space showed that the model was not restricted by this objective.

Originality/value: The value proposition of this work is presented in a case study comparison of our multi-objective model against a single objective model from literature. The multi-objective model dominates the literature model giving invaluable insights to possible improvements to previous research work.

Keywords: sustainable manufacturing, multi-objective optimization, dynamic cellular manufacturing systems, genetic algorithm (NSGA-II), penalty approach

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1. Introduction

Sustainable Manufacturing (SM) is defined as producing goods through activities that meet present needs without compromising the ability of future generations to do likewise (Yong-Chan & Xirouchakis, 2015). This aspect extends to the three pillars of sustainability which are environmental constraints, social impacts, and financial limitations. An increasing amount of research is conducted on integrating these three aspects of sustainability for improved efficiencies in Manufacturing Systems (MS). Cellular Manufacturing (CM) is a production technique where products are manufactured in small, self-contained units known as cells. Cellular Manufacturing Systems (CMS) are a type of MS that is organized around the production of specific product families, or groups of similar products (Cerqueus, Paolo, Damien & Xavier, 2020). These systems involve the use of small, flexible teams of workers and machines that are dedicated to producing a specific set of products or components. There are several types of CMS, including single-cell systems, where all the activities needed to produce a product are carried out in a single location, and multi-cell systems, where different cells are dedicated to dissimilar stages of the production process (Asokan, Prabhakaran & Kumar, 2001). To be successful, CMS require careful planning and coordination, as well as well-trained and motivated workers.

CMS typically involve lean manufacturing principles, which utilize techniques such as Just In Time (JIT) manufacturing, where materials arrive and the production facility just when they are required, and Kanban systems, which use visual signals to indicate when materials or components need to be replenished. CMS can improve efficiency and reduce cycle times by eliminating unnecessary processing steps and minimizing the need for material handling (Cerqueus et al. 2020). They also allow for greater flexibility and responsiveness to changing product conditions, as fixtures can be reconfigured to produce assorted products in respond to changes in market demand. Another benefit of CMS is that they can improve the quality of products, as teams are able to identify and address quality issues more quickly. Accumulating conveyors and/or station buffers are often used in CMS to avoid bottlenecks during breakdowns or routine maintenance operations. Furthermore, CMS help increase accountability, as team members are responsible for the performance of their cell. Also, they can improve safety in the workplace by allowing teams to focus on a specific set of products, which can reduce the risk of accidents and injuries (Lokesh & Promod, 2011).

Dynamic Cellular Manufacturing Systems (DCMS) are an extension of CMS that are reconfigured periodically to suit demand. Whenever the physical layout or process flow of a CMS is changed from period to period, the system is referred to as a DCMS. The reconfiguration of DCMS enhances the effectiveness of CMS in adapting to changes and improved efficiency. As consumer trends lean towards products with a shorter life span and more customization, a particular layout may not always be feasible when demand changes, hence, the need for DCMS has never been greater. Maintaining an effective DCMS requires careful consideration of all the factors that affect the product. DCMS present more control for manufacturers to plan for production and factory maintenance. This improved flexibility makes manufacturers more competitive in the market on more than just one objective, which is the driving reason for implementing DCMS (Alimian, Ghezavati & Tavakkoli-Moghaddam, 2020).

The need for periodic reconfiguration of manufacturing systems is clear and replete throughout literature, however, the need for this study is founded in the incorporation of all three aspects of sustainability within reconfiguration planning. Because most researchers focused primarily on the economic factors of production during optimization, there exists a gap in literature which includes all three pillars of sustainability in a single reconfiguration model. Since manufacturers need assurances that changes to their existing systems are practical and not only theoretically based; this study uses industry-based metrics and impact factors to provide confidence in suggested directions. Although a manufacturing layout may be optimal for a set of initial conditions, it can become outdated and contain bottlenecks and/or inefficiencies over time as demands or products change; hence, reconfiguring DCMS becomes vital. Our study of reconfiguration planning is aimed at enhancing optimality in industry.

2. Literature Review

Combining SM, which delivers cost savings, resource conservation, and enhanced efficiency; with DCMS known for its flexibility, adaptability, and customizability, gives organizations a competitive market edge. Researchers have noted the significance of addressing SM and DCMS simultaneously (Zhao & Wu, 2000). Compliance with the world's Sustainable Development Goals (SDGs), requires manufacturers to brainstorm ways to adhere to new and/or stricter sustainability regulations. Goals 8 and 12 from the SDGs focus on promoting decent work and economic growth, and responsible consumption and production respectively. Sustainability is the union of its three pillar aspects namely, economic factors, social influences, and environmental constraints as depicted in Figure 1.

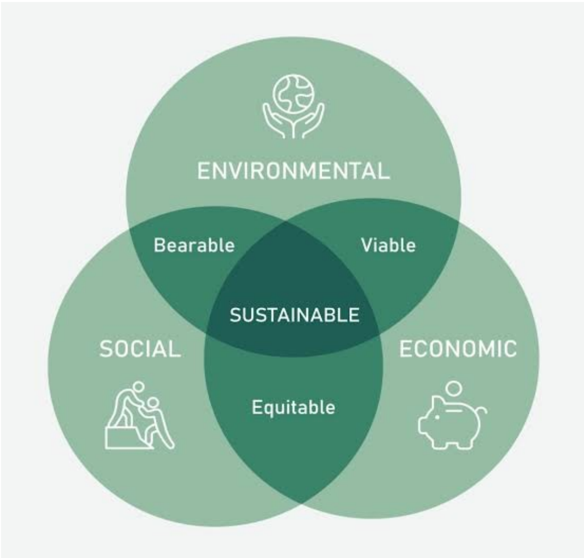

Figure 1. Pillars of sustainability: Social, Economic, and Environmental

Each of these aspects uniquely affects manufacturing technologies and practices, leading to multi-objective problems that often require careful planning to find the most optimal routing for a MS. With the globalization of today's markets and the evolving workforce due to automation, it becomes increasingly difficult to plan the best routing without the aid of optimization techniques and strategies. The use of data analytics and the adoption of continuous improvement methods, such as Kanban Boards, Kaizen, Lean Manufacturing, Six Sigma, and other digital technologies is helpful in supporting the adoption of more sustainable practices. These strategies help manufacturers identify bottlenecks, eliminate waste, and improve efficiency in production processes (Yong-Chan & Xirouchakis, 2015).

Research on sustainability oriented DCMS models has evolved from a primary focus on economic efficiency toward more holistic frameworks that integrate environmental and social objectives (Aljuneidi & Bulgak, 2016). Early models typically addressed cost minimization and basic cell reconfiguration, with limited attention to sustainability's three pillars often treating environmental and social aspects as secondary or as constraints rather than explicit objectives (Niakan, Baboli, Moyaux & Botta-Genoulaz, 2014). Recent studies have advanced mathematical formulations, employing mixed-integer linear or nonlinear programming to capture dynamic layouts, (Sibanda & Padayachee, 2024) uncertain demand, and hybrid manufacturing processes, while explicitly modeling energy consumption, emissions, and social impacts such as labor conditions and job opportunities

(Jafarzadeh, Khalili & Shoja, 2022; Almasarwah, Abdelall, Bhutta & Saraireh, 2025). Optimization approaches have shifted from exact solvers, which struggle with computational complexity in large scale problems, to sophisticated meta-heuristics like NSGA-II and simulated annealing, enabling multi-objective, large dimension instances with improved efficiency and solution quality (Lamba, Kumar, Mishra & Rajput, 2020). Despite these advances, a critical gap remains: many models still inadequately address the full integration of all three sustainability pillars, often prioritizing economic and environmental objectives while relegating social factors to constraints or proxies. Furthermore, uncertainty, whether in demand, process times, or sustainability parameters, has only recently begun to be incorporated, using fuzzy logic or robust optimization, but remains underexplored in multi-objective contexts (Jafarzadeh et al, 2022). Literature also highlights a lack of comprehensive frameworks that simultaneously optimize for cost, environmental impact, and social responsibility under real-world uncertainty, especially in closed-loop or hybrid systems (Telegraphi & Bulgak, 2020). This gap justifies the need for rigorous, multi-objective models that explicitly and equitably treat all sustainability dimensions, leveraging advanced meta-heuristics and robust optimization to address the complexity and uncertainty inherent in modern DCMS. This approach aligns with the pressing industrial and societal demand for truly sustainable MS (Pérez-Gosende, Mula & Díaz-Madroñero, 2020).

The adoption of more sustainable practices in CMS requires careful planning and coordination, as well as the establishment of clear goals and objectives. Furthermore, sustainability can be measured in many ways. Yong-Chan et.al emphasized the need to include environmental metrics of energy use and waste management while optimizing CMS with sustainability considerations. (Khezri, Hichem & Lyes, 2019) studied the sustainability of CMS, focusing on liquid waste, and gas emissions. (Khettabi, Lyes & Mohamed, 2021) employed a multi-objective approach using NSGA-II and NSGA-III to minimize hazardous liquid waste, greenhouse gas emissions, production time, and costs. Their findings revealed that energy usage is influenced by production planning and related system configurations, accounting for idle times, setup times, part or tool transfers. A comprehensive review of literature is given in the work of (Pérez-Gosende, Mula & Díaz-Madroñero, 2021), however, Table 1 summarizes some recent studies on sustainability and their focused metrics.

Year	Focus	Approach
(Khettabi, Lyes & Boutiche, 2022)	Hazardous liquid waste, Carbon emission	NSGA-II, New NSGA-III
(Khettabi et al., 2021)	Carbon emission	GA, TOPSIS
(Khezri, Hichem & Lyes, 2021)	Energy consumption, Waste	AUGECON, NSGA-II, SPEA-II
(Massimi, Amirhossein, Hichem & Lyes, 2020)	Energy consumption	Mathematical
(Cerqueus et al., 2020)	Energy cost	Genetic Algorithm
(Khezri et al., 2019)	Energy consumption, Waste	Augmented ε-constraint
(Liu, Rongfan, Zhanguo, Chengbin & Xiaoyi, 2018)	Energy cost	NSGA-II & MOSA
(Huang, Badurdeen & Jawahir, 2018)	Energy consumption, Water consumption	Mathematical
(Jiafeng, Khalgui, Wassim, Frey, Hon, Wu et al., 2015)	Energy efficiency	Reconfigurable timed net condition
(Yong-Chan & Xirouchakis, 2015)	Energy consumption	Muti-objective optimisation

Table 1. Recent literature on CMS sustainability

As more companies adopt the net zero standards, it becomes imperative that the environmental effects of manufacturing be included in the objective of optimization models for MS. This is in the form of waste reduction, the introduction of more renewable energy sources, newer technologies, and reduced greenhouse gas emissions. The Science Based Targets initiative (SBTi) has established a global standard to provide direction to organizations on achieving net-zero targets through a guided approach for setting near-term and long-term goals. Its goal is to encourage companies to halve their carbon emissions before 2030 and reduce their emissions entirely, to net-zero standards by 2050. The standard classifies greenhouse gas emissions into three categories namely: Scope1, 2, and 3 emissions. Each category encapsulates production activities differently for the different sectors in industry in an accepted standardization (Science Based Targets, 2021a).

Scope 1 emissions are direct emissions originating from sources owned or controlled by an organization, such as those produced by fossil fuel combustion in company-owned boilers or vehicles. Scope 2 emissions are indirect emissions resulting from the generation of purchased energy consumed by the organization, such as electricity, heat, or steam typically acquired from a utility provider. Scope 3 emissions are also indirect but arise from the organization's activities at sources it does not own or control, including emissions from raw material production, product transportation, and waste disposal. Scope 3 emissions often represent the largest portion of an organization's total emissions and can be the most difficult to measure and reduce (Science Based Targets, 2021a). This study concentrates on optimizing the performance of CMS by examining carbon emissions from overall production activity as a general, all-inclusive measure of sustainability. Production activity considered includes emissions from material handling, part processing, machine life cycle, and machine idle. The unit of measurement employed is metric tons of carbon emitted, denoted as $kgCO_2$.

3. Mathematical Model

3.1. Model Notation

We present the model notation as:

Sets:

t – time index, $h = 1 \ldots T$ – total number of Periods

i – part index, $p = 1 \ldots I_t$

j – index of operations on parts, $j = 1 \ldots O_i$ – total number of operations needed for part i

k – machine index, $k = 1 \ldots K$ – total number of machines

l – cell index, $l = 1 \ldots L$ – total number of cells

Decision variables:

x_{jiklt} – 1 if operation j of part i by machine k is done in cell l during time t, otherwise 0

N_{klt} – number of type k machines placed in cell l at time t

K^{+}_{klt} – number of type k machines added to cell l at the beginning of time t

K^{-}_{klt} – number of type k machines removed from cell l at the end of time t

a_{jik} – 1 if operation j of part i can be done on machine k; otherwise 0

Parameters:

LB = Cell size lower bound

UB = Cell size upper bound

D_{it} = Demand of part i during period t

B_i^{inter} = Intercell batch size for part i

B_i^{intra} = Intracell batch size for part i

H_k = Available time on machine k (hr)

h_{jik} = time for operation j of part i on machine k (hr)

α_k = Overhead cost of machine type k

β_k = Variable operating cost for each unit time on machine k (R/hr)

γ^{inter} = Batch intercell material handling cost

γ^{intra} = Batch intracell material handling cost

δ_k = Relocation cost for machine type k

φ^{inter} = Batch intercell carbon emissions ($kgCO_2$)

τ_k = Carbon emissions from adding and removing machine type m ($kgCO_2$)

μ_k = Carbon emissions from idle time of machine type k ($kgCO_2$/hr)

ε_k = Variable carbon emissions for each operating unit time, on machine type k ($kgCO_2$/hr)

σ_k = Carbon emissions from relocating machine type k ($kgCO_2$)

q = Workload balancing factor (taken as ± 0.75 for 75 %)

η = maximum number of different operations an operator can be assigned (taken as 3)

3.2. Model Description

Minimize:

$$Z_1 = \sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{k=1}^{K}\mu_k\left\{\sum_{i=1}^{I}\sum_{j=1}^{OP} T_k N_{klt} - D_{it}t_{jik}x_{jiklt}\right\} + \frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{OP-1}\sum_{l=1}^{L}\left[\frac{D_{it}}{B_i^{inter}}\right]\varphi^{inter}\left|\sum_{k=1}^{K}x_{(j+1)iklt} - \sum_{k=1}^{K}x_{jiklt}\right| + \sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{k=1}^{K}\tau_k\left|N_{kl(t+1)} - N_{klt}\right| + \frac{1}{2}\sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{l=1}^{L}\sigma_k(K^+{}_{klt} + K^-{}_{klt}) \tag{1}$$

$$Z_2 = \sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{i=1}^{I}\sum_{j=1}^{Op}\sum_{k=1}^{K}\beta_k D_{it}t_{jpm}x_{jiklt} + \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{l=1}^{L}N_{klt}\alpha_k + \frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{OP-1}\sum_{l=1}^{L}\left[\frac{D_{it}}{B_i^{inter}}\right]\gamma^{inter}\left|\sum_{k=1}^{K}x_{(j+1)iklt} - \sum_{k=1}^{K}x_{jiklt}\right| + \frac{1}{2}\sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{l=1}^{L}\delta_k(K^+{}_{klt} + K^-{}_{klt}) + \frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{OP-1}\sum_{l=1}^{L}\left[\frac{D_{it}}{B_i^{intra}}\right]\gamma^{intra}\left(\sum_{k=1}^{K}\left|x_{(j+1)iklt} - x_{jiklt}\right| - \left|\sum_{k=1}^{K}x_{(j+1)ilt} - \sum_{k=1}^{K}x_{jilt}\right|\right) \tag{2}$$

Subject to:

$$\sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{j=1}^{OP}x_{jiklt} \geq \frac{q}{L}\sum_{l=1}^{L}\sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{j=1}^{OP}x_{jiklt} \qquad \forall\, l,t \tag{3}$$

$$\sum_{l=1}^{L}\sum_{k=1}^{K}a_{jik}x_{jiklt} = 1 \qquad \forall\, j,i,t \tag{4}$$

$$LB \leq \sum_{k=1}^{K}N_{klt} \leq UB \qquad \forall\, l,t \tag{5}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{OP} D_{it}t_{jik}x_{jiklt} \leq T_k N_{klt} \quad \forall\, k,l,t \tag{6}$$

$$N_{kl(t-1)} + K^{+}{}_{klt} - K^{-}{}_{klt} = N_{klt} \ \forall\, k,l,t \tag{7}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{OP} x_{jiklt} \leq \eta N_{klt} \quad \forall\, k,l,t \tag{8}$$

$$x_{jiklt} \in \{0,1\}, N_{klt}, K^{+}{}_{klt}, K^{-}{}_{klt} \in \{0, \mathbb{Z}^{+}\} \tag{9}$$

The first objective function (1) minimizes the environmental impact measured in $kgCO_2$. It consists of four components: machine idling emissions, intercell material handling emissions, machine relocation emissions, and machine lifecycle emissions. The second objective function (2) minimizes the total cost in ZAR, which includes machine operational costs, overhead/rental costs, intercell material handling costs, machine relocation costs, and intracell material handling costs.

Constraint (3) balances the workload across cells for social equity. Constraint (4) ensures each part operation is assigned to a single machine and processed once. Constraint (5) sets lower and upper bounds on the number of machines per cell. Constraint (6) guarantees machine capacity limits are not exceeded. Constraint (7) enforces accurate machine placement and relocation calculations across demand periods. Constraint (8) limits the number of part operations assigned to an operator.

4. Solution Approach

4.1. Scope

With the backdrop of the SBTi, we propose an extension to a traditional single objective optimization model to solving a DCMS. We present a bi-objective optimization approach which seeks to minimize the economic cost of production and reduce the environmental effects of the system over the planning periods. The environmental objective will seek to minimize a combination of scope 1, 2, and 3 emissions of the system. Scope 1 emissions will be interpreted as the emissions from the number of machines in the entire system. Scope 2 emissions will be interpreted as emissions from the amount of energy used in material handling and machine utilization. Scope 3 emissions will be interpreted as emissions from the amount of fuel used in intercell material handling. Furthermore, we incorporate a social objective as a third objective of the model in the form of additional constraints. The constraints will ensure that the resulting solution is within a predefined range for the operators and is balanced for the entire staff.

4.2. Solvers

Various approaches have been employed to solve DCMS models in literature, each with its own strengths and weaknesses depending on problem complexity, the number of factors considered, and desired outcomes. Key benchmarks for these techniques include solution generation speed and quality. As noted by (Defersha & Chen, 2008), and widely recognized in the field, certain techniques are better suited for specific problem sizes. While early researchers often relied on commercial software based on mathematical programming algorithms, meta-heuristic techniques have gained increasing popularity due to their adaptability to diverse problem structures.

Other aspects for consideration when selecting a solver are performance metrics, available computational resources, customization, and cost of licensing. Researchers evaluate the quality of solutions produced by solvers in terms of objective function values, converging time, and determine the solver's ability to find solutions consistently across different problem instances and settings, including how well the solver performs as problem size or complexity increases (Cao & Chen, 2004).

4.3. Penalty Function

To evaluate solutions, a non-dominated sorting method combined with a penalty approach was employed. Solutions were graded based on three primary criteria: penalty value, rank, and crowding distance. Additional solution attributes considered included uniqueness, dominance count, and domination count. For a given solution Z, where A, A_{eq}, b, and b_{eq} represent the problem constraints, and M is a large positive value, the penalty expression for inequality constraints was calculated as shown in Equation (10). This approach is similar to that used by (Cao & Chen, 2004):

$$P_1(Z) = M * \max\,[0, [\,A - b]]^2 \tag{10}$$

the formulation of the penalty expression for the equality constraints was Equation (11) [24]:

$$P_2(Z) = M * sum\left\{\left[sum[\,A_{eq} - b_{eq}\,]\right]^2\right\} \tag{11}$$

4.4. Unique Non-Dominated Sorting

To prevent premature convergence and reduce computational time, the weighting of objective functions was implemented using principles from the NSGA-II approach. The base NSGA-II method was further refined by sorting the combined population (parent, offspring, and mutant) to select the best unique solutions for the next generation. This modification enhanced solution exploration and population diversity. The approach initially ranks solutions based on Pareto fronts. Subsequently, solutions within each front are sorted by their crowding distance, a measure of solution distribution. The unique solutions are selected for the next generation. If unique solutions were fewer that the population size, duplicate solutions from the top-ranked solutions are added to fill the population. (Zhang, Li & Zhang, 2008).

Dominance relationships between solutions are determined based on objective function values. For a single minimization objective, solution $Z(x_1)$ dominates solution $Z(x_2)$ if $Z(x_1)$ objective function value is smaller than $Z(x_2)$. For multiple minimization objectives, A dominates B only if A is no worse than B in all objectives and strictly better in at least one objective. When a second minimization objective is introduced, $Z(x_1, y_1)$ dominates $Z(x_2, y_2)$ if ($x_1 \leq x_2$ and $y_1 \leq y_2$) and ($x_1 < x_2$ or $y_1 < y_2$). The Boolean result was used to identify non-dominated solutions across populations and assign rank accordingly. The crowding distance, calculated using Equation (12), is a measure of the average distance between neighbouring solutions in the objective space. Here N is the font count for each iterative generation, While the Pareto front is represented by F, and M is the total number of objectives, the crowding distance (d_i) for each solution was calculated using the equation Equation (12):

$$d_i = \sum_{n=1}^{N}\sum_{m=1}^{M}\frac{F_n(Z_m)(i+1) - F_n(Z_m)(i-1)}{F_n^{\,max} - F_n^{\,min}}\ \forall\, i \tag{12}$$

4.5. Genetic Algorithm

Evidently, the GA emerges as the optimal solver for the sustainable model due to its distinct strengths over other solvers in several key aspects. This is owing to its adaptability, population-based exploration, efficient handling of constraints, effectiveness in multi-objective optimization, customization options, scalability, and parallelization capabilities. Its ability to address a wide array of optimization challenges makes GA the optimal choice to achieve robust and high-quality solutions. GAs are a type of evolutionary metaheuristic technique that iteratively improves a population of potential solutions. Starting with a randomly generated initial population, GAs apply genetic operators like crossover and mutation to create new generations of solutions. (Berlato, Montanha & Simon, 2006). The pseudo code for the developed GA is detailed in Figure 2.

4.6. Repair Function

Repair functions, also known as constraint handling techniques, or repair mechanisms, are essential components in GAs for addressing constraint violations during the evolution process. When a solution generated by the GA violates problem constraints, it can either be automatically discarded, or a repair function is applied to modify the solution such that it satisfies the constraints while preserving its quality as much as possible. Effective constraint handling mechanisms are crucial for ensuring the GA's robustness and ability to handle real-world optimization problems with complex constraints. Experimentation and tuning of repair functions are often necessary to find the most suitable approach for a given problem domain. Penalty-based repair functions penalize solutions based on the degree of constraint violation. In this approach, the objective function is augmented with penalty terms that penalize violations of constraints. The GA then optimizes the penalized objective function, indirectly encouraging solutions to satisfy the constraints. Repair by resampling involves randomly resampling or generating new values for violated variables to bring the solution back into feasibility. This approach requires careful balancing between exploration and exploitation to avoid excessive randomness while exploring the solution space (Amjad, Butt, Anjum, Chaudhry, Faping & Khan, 2020).

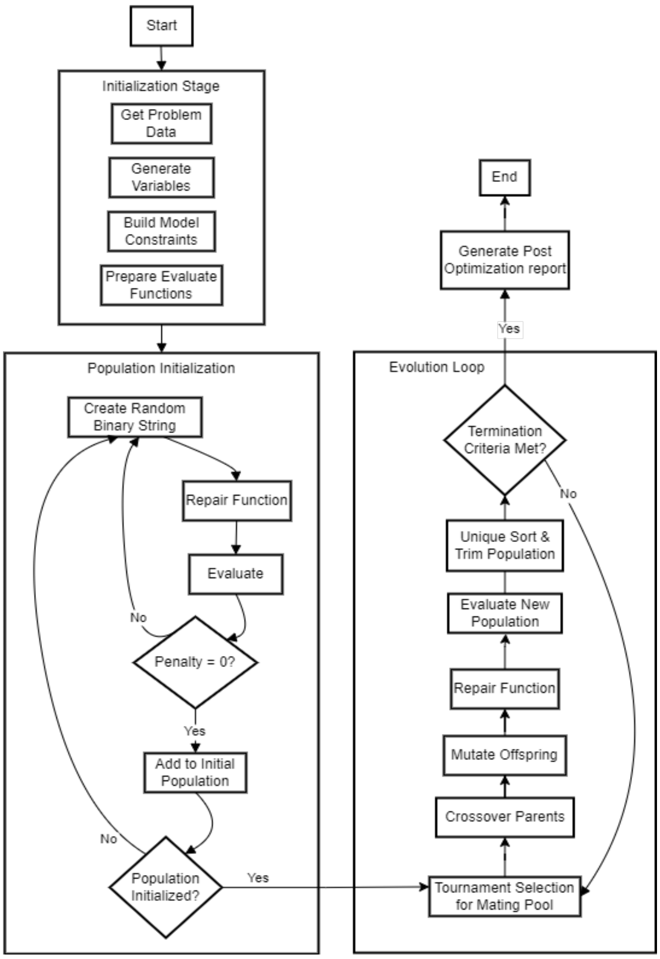

Figure 2. GA pseudo code

A hybrid repair function was developed to rectify solutions that violated any constraint during initialization, crossover, or mutation. This function combines aspects of resampling and penalty-based approaches. The repair process commences by addressing primary variable violations of constraint (6). Subsequently, machines are assigned to cells in accordance with constraint (7). Unallocated machines are removed, and demand periods are combined to determine machine relocation variables. Repaired solutions are then evaluated against cell size constraints (8). The penalty approach effectively maintains most constraints, however, cell upper bound constraints proved challenging to repair without significantly increasing computational effort. Therefore, solutions that still violated constraints after the initial repair were discarded. To address cell lower bound violations, a minimal number of random machines were added to the cell. This repair process is shown in Figure 3.

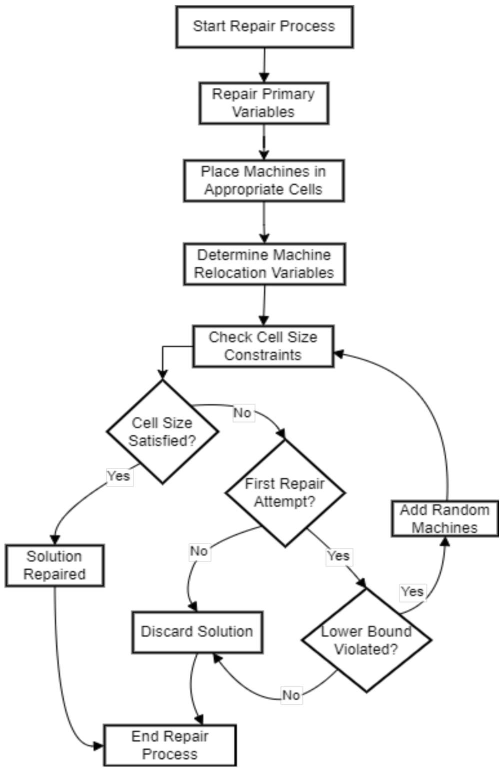

Figure 3. Repair function pseudo code

5. Case Study

5.1. Problem Description

Traditionally, optimization efforts have focused predominantly on minimizing economic costs, overlooking the crucial aspects of environmental sustainability, and social responsibility. Few studies have explored the integration of environmental objectives within optimization models, while others have also considered a social objective or limitation in other models, however, a significant research gap exists where all three aspects are considered simultaneously. In response to this gap, our study introduces a dual objective model that integrates economic cost minimization with environmental emissions reduction, and social constraints on the workforce. By comparing the performance of this novel approach against the single objective model from (Safaei, Saidi-Mehrabad, Tavakkoli-Moghaddam & Sassani, 2007) we aim to elucidate the benefits of incorporating environmental, and social considerations into optimization models. The data for this problem is given in Table 2 to 4.

Op	PARTS							
	P1	P2	P3	P4	P5	P6	P7	P8
J1	[0.68]M2 [0.55]M5	[0.67]M2 [0.79]M5	[0.13]M4 [0.36]M6	[0.55]M2 [0.82]M3	[0.71]M2 [0.17]M5	[0.72]M2 [0.81]M6	[0.44]M2 [0.76]M5	[0.84]M4 [0.20]M5
J2	[0.61]M2 [0.63]M3	[0.23]M2 [0.48]M3	[0.19]M2 [0.89]M5	[0.58]M2 [0.78]M6	[0.49]M4 [0.45]M6	[0.57]M1 [0.48]M6	[0.97]M3 [0.47]M4	[0.17]M2 [0.86]M4
J3	[0.88]M3 [0.63]M4	[0.24]M2 [0.57]M3	[0.58]M4 [0.96]M5	[0.76]M1 [0.26]M5	[0.65]M5 [0.59]M6	[0.47]M2 [0.12]M5	[0.28]M2 [0.86]M5	[0.54]M1 [0.15]M3
B_p^{inter} B_p^{intra}	5 25	5 25	4 20	7 35	4 20	8 40	8 40	6 30
	γ^{inter} = R 25 (ZAR)		γ^{intra} = R 5 (ZAR)		φ^{inter} = 45 kgCO2		μ_m = 0.958 kgCO2/hr	

Table 2. Case study part production data

N_{mch} Machine	T_m Available Time (hr)	α_m Overhead Cost (ZAR)	β_m Operation Cost (ZAR)	δ_m Relocation Cost (ZAR)	τ_m Sourcing Emissions ($kgCO_2$)	σ_m Relocation Emissions ($kgCO_2$)
M1	700	1200	6	600	6200	3100
M2	700	1400	3	700	5320	2660
M3	700	1500	7	750	4960	1500
M4	700	1400	4	700	5320	2660
M5	700	1200	2	600	6200	3100
M6	700	1600	8	800	4650	2325

Table 3. Part production data

Part	Period 1	Period 2	Period 3
P1	200	500	600
P2	0	450	0
P3	0	0	600
P4	650	500	0
P5	350	0	750
P6	600	500	350
P7	550	200	300
P8	600	450	350

Table 4. Part demand data

5.2. Optimization Results

The case study was solved on MATLAB R2021a running on a computer with a 2.70 GHz 7th generation Intel i7 processor, with 2 cores, and 8 GB RAM. The algorithm ran for a thousand generations for exhaustive exploration.

Through a rigorous simulation, the study demonstrates the superiority of the dual objective model over its single objective counterpart. The findings reveal that the dual objective model not only achieves superior economic cost savings, but also significantly reduces environmental emissions, thus presenting a more sustainable and efficient solution. Figure 4 shows the difference between the solution from literature and the solution generated by the sustainable model. Evidently, the dual objective solution dominates the single objective solution. Furthermore, the mental pressure on the staff is reduced as well. The study presents a compelling argument for the adoption of dual objective optimization models in DCMS. By concurrently addressing economic cost minimization, environmental emissions reduction, and improved social responsibility, the dual objective model offers a more holistic and sustainable approach to system optimization. These findings not only contribute to the theoretical understanding of DCMS but also provide practical insights for industry practitioners seeking to enhance operational efficiency while mitigating environmental impact. Table 5 to 7 detail the generated solution which can be contrasted to that presented by (Safaei et.al., 2007).

5.3. Sensitivity Analysis

The performance of a GA can be influenced by various input parameter settings including crossover rate, mutation rate, mutation operator, crossover operator, parent selection techniques, population trimming strategies, and termination criteria. Furthermore, there could be interactions between these parameters in the optimization process. Hence, a sensitivity analysis was conducted by changing a single of the parameters from the original solution and running the GA for 1000 generations as was done in the original solution. Table 8 details the parameters which were changed and shows the results.

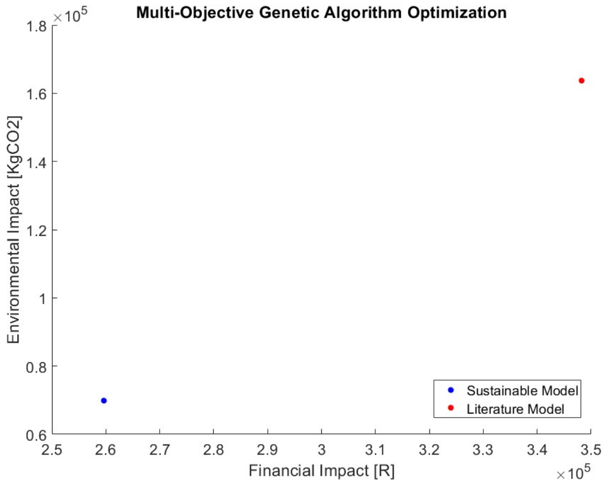

Figure 4. Graph of sustainable model vs literature model

Cell Number	Machine Number	PARTS						Demand Period
		P1	P4	P5	P6	P7	P8	
1	M3	2,3					3	1
	M5		3	1				
	M6			2,3	2			
2	(2)M2		1,2		1	3		
	M5	1			3	1		
3	(2)M4					2	1,2	

Table 5. Sustainable model period 1 planning

Cell Number	Machine Number	PARTS						Demand Period
		P1	P2	P4	P6	P7	P8	
2	(2)M2	1,2	1,2,3					2
	M5			3	3	1		
	M6				1,2			
3	M2			1,2		3		
	M3					2	3	
	(2)M4	3					1,2	

Table 6. Sustainable model period 2 planning

Cell Number	Machine Number	PARTS						Demand Period
		P1	P3	P5	P6	P7	P8	
2	(2)M5		2,3	1	3		1	3
	(2)M6			2,3	1,2			
3	(2) M2	1,2				1,3	2	
	M3						3	
	M4	3	1			2		

Table 7. Sustainable model period 3 planning

Parameter	No. of solutions	Machine Utilization %	Min Production Time	Min Obj1 Val	Min Obj2 Val
Original	128	61 ~ 70	689	342518	105210
Crossover rate = 0.6	128	60 ~72	689	342518	105210
Crossover rate = 1	128	60 ~72.2	689	342518	105210
Mu = 0.01	187	63 ~ 74.2	672	306495	81215
Mu = 0.025	200	60.7 ~ 69.8	673	309974	96322
Mu = 0.075	53	66.9 ~ 73.8	664	318422	118573
Mu = 0.1	89	59.5 ~ 68.7	673	319915	123929
Generations = 500	147	60 ~ 70	689	343074	127369
Population Size 150	19	68.2 ~ 75.3	673	322068	110356
Population Size 250	35	66 ~ 73.7	694	307609	104390
Cell Size LB = 2	200	64 ~73.9	672	310588	96082

Table 8. Sensitivity analysis on problem 3

A final sorting of all generated solutions was conducted at the conclusion of the GA sensitivity study. There were 1058 unique solutions altogether, from which 211 were in the first Pareto front after sorting. Within that front, the best solution was selected based on production time and machine utilization characteristics. The solution with the highest machine utilization had the lowest production time. This solution was the most financially conservative solution from the lot suggesting a strong relationship between machine utilization and the financial objective.

To scrutinize any biases in the solution pattern, varying changes were made to the problem parameters, collecting the results after each iteration. The changes were focused on machine available time, material handling emissions, and material handling cost, because these parameters affect the values of both objective functions. Figure 5 shows the results from each iteration with the legend showing each altered variable. The combined solution from the GA sensitivity was then plotted to show the variance of each iteration from the original solution.

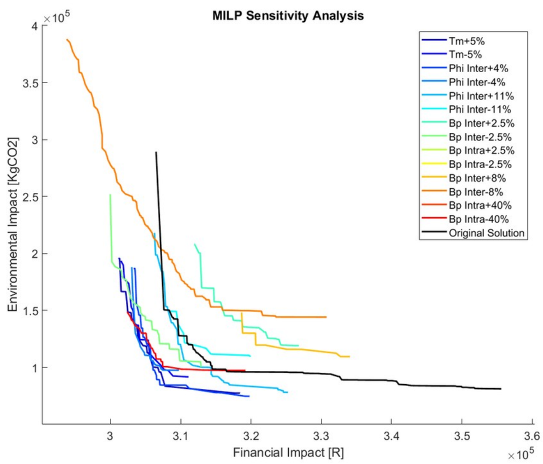

Figure 5. MILP sensitivity analysis

It is noted that the concave shape of the resulting Pareto is consistent across the different iterations. This insight is the most significant finding as it confirms the relationship between the two objective functions over the different parameter settings. The clustering of the plots around the same region shows the similarity of the model's behavior, and that the solution space is not restricted by the constraints, which is where the social objective is contained. Another significant insight to be gained from the analysis is that the most influential parameters are the available time on the machines, and the material handling parameters. Changing the intercell part batch emissions has little deviation from the original solution. Holistically, the analysis shows how changes in parameters would affect the solution, giving decision makers insight should any parameters be undefined in the system they are attempting to optimize. With this study they may predict the behavior and influence of each term in their system.

6. Discussion

Noting that the case study from literature focused solely on minimizing the economical impact of production, a computational efficiency comparison of the studies would be biased. However, extending the problem by introducing an environmental objective creates a new perspective that adds further insights to the posed solution. Firstly, the added dimension revealed the existence of solutions that are not only more economically preferable, but also of a significantly reduced environmental footprint as shown in Figure 4. Secondly, the extension shows that previous optimisation attempts were stuck in a local minima. The consideration of the environmental impact guided the GA to escape local minima and find dominant configurations in the solution search space. The common shape of each resultant Pareto plot shown in Figure 5 is a strong indicator of the relationship between environmental impact and the cost of production. The concave relationship shows that there is a trade-off along the Pareto plot. As environmental impact decreases, the economic implications increase; the opposite can be said when environmental impact increases. This insight is strongly supported by the sensitivity analysis as multiple iterations revealed similar shaped Pareto plots.

The practical implications of this study suggest that manufacturers need to consider not only the cost of production, but also the environmental footprint of planned activity, including the social impact on the workforce. Objectively, there are limitations to this paper's methodological approach, the GA solver being one. From the sensitivity study different solution plots were generated from changing model parameters. Hence, it is noted that not all parameter combinations were explored. It would be ideal to compare results from other metaheuristic, and non-metaheuristic solvers for reference. Another limitation of this study is data bias from the singularity of the case study. We acknowledge that other insights that have not been captured herewith may be found in larger models with different model assumptions.

7. Conclusion

The paper proposes incorporating all three pillars of sustainability when solving CMS. Emission factors were used to simulate the environmental contributions of key processes, with emissions reckoned in metric tons of carbon dioxide (kg CO_2). A minimization mathematical model of a multi-objective nature was developed. A bi-objective NSGA-II was implemented as the solver approach. The penalty approach was used to enforce model constraints. A custom repair function was added to the solver to recover solutions that violated constraints. The NSGA-II was modified to prioritize unique solutions before allowing duplicate solutions when trimming the population. A case study from literature was presented. Results from the optimization supported the hypothesis that environmentally friendly options share a concave relationship with their financially conservative counterparts. A sensitivity analysis showed that the results were not solver biased, and identified which parameters directly influenced the final solution population. The research showed that there exists a tradeoff between the different aspects of sustainability, and manufacturers need to implement a multi-objective model, such as the one presented, to cater for all three pillars. Future developments to the work presented include layout planning, intracell workload balancing, and production scheduling. Practical implications for industry include the incorporation of renewable energy sources for material handling services, and the reduction of carbon emissions by reducing machine idle.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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