Genetic Algorithms for Optimized Selection of Biodegradable Polymers in Sustainable Manufacturing Processes

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Abstract – Sustainable Manufacturing Practices (SMP), particularly in the selection of materials, have become essential due to environmental issues caused by the expansion of industry. Compared to conventional polymers, biodegradable Polymer Materials (BPM) are growing more commonly as an approach to reducing trash pollution. Suitable materials can be challenging due to numerous considerations, like ecological impact, expenditure, and material properties. When addressing sophisticated trade-offs, standard approaches drop. To compete with such challenges, employing Genetic Algorithms (GA) may be more successful, as they have their foundation in the basic concepts of biological development and the natural selection process. With a focus on BPM, this study provides a GA model for optimal packaging substance selection. Out of the four algorithms for computation used for practical testing—PSO, ACO, and SA—the GA model is the most effective. The findings demonstrate that GA can be used to enhance SMP and performs well in enormous search spaces that contain numerous different combinations of materials.

Keywords – Sustainable Manufacturing Practices, Machine Learning, Environmental Pollution, Biodegradable Polymer Materials, Genetic Algorithms, PSO, ACO, Simulated Annealing.

I. INTRODUCTION

Sustainable Manufacturing Practices (SMP) have been gradually and systematically finding progress throughout all aspects of the manufacturing industry in the past few decades, signifying an important change in the contemporary industrial sector. Preventing the real-life environmental consequences associated with products produced with energy sources from petroleum and other petroleum products and satisfying the constantly evolving needs of users and government officials were the primary drivers of this advancement [1]. The SMP idea, which relies on the concept of reducing negative environmental effects at all levels of manufacturing while simultaneously improving resources and conservation of energy, has long been connected with the transformation of the cycle of operation. The selection and use of materials from nature is a significant manufacturing industry step by step which demands thoughtful consideration in order to accomplish a sufficient level of environmentally conscious development [2]. This is because this decision directly influences the economic, social, and environmental aspects of accountability for the environment. Additional engaging than typical polymers that are used Biodegradable Polymer Materials (BPM) provides an innovative solution to waste reduction by degrading apart into innocuous byproducts. This pressing requirement motivated the development of BPM.

Following the recognition that BPM has a chance to provide several benefits, the task of identifying the accurate BPM is plagued with vital challenges. These difficulties originate from various material features, environmental values, and financial considerations that must be addressed [3]. The mathematical models that are presently in use for choosing materials are all reliant on either linear or static model-based systems for decision-making due to the specifics of the task at face. A framework of this helpful, on the contrary, fails to consider multiple trade-offs and variability of substance performance over time [4]. In addition, such models cannot efficiently explore the extensive search spaces mainly defined by the combinations of material variables. This leads to poor selection decisions, which can cause the model to fail to satisfy the criteria that are required for achieving Environmental Sustainability (ES).

Genetic algorithms, or GA, are now acceptable for maintaining ES and identifying suitable BPM [5]. In following the concepts of biological selection and the evolution of genes, the GA framework can model the steps of evolution by applying methods such as selection, crossover, and mutation, which are performed on a sample of candidate solutions [6]. Through this iterative process, the GA model in their process effectively involves the exploration of diverse combinations of material properties. The selection of materials through GA ensures a dynamic adaptation of finding optimal or near-optimal solutions that satisfy the environmental impact, performance, and cost factors. By employing the computational intelligence of GAs, manufacturing industries can efficiently make material selection decisions that align with sustainability principles.

Built on the above motivation, the proposed work in this paper involves the application of GA to optimize the selection of BPM in Sustainable Manufacturing (SM). The GA method involves simulating the process involved in natural evolution to identify optimal solutions that balance factors like environmental benefits, material performance, and cost. This optimal balancing process is achieved by evolving a population of candidate solutions, which is measured using an adaptive fitness function that includes the scores of environmental impact, mechanical properties, and economic viability. The proposed work's applicability is experimented with using a case study involving a packaging industry in migrating to manufacturing packages using eco-friendly materials, and the models performed up to the expectation, thereby demonstrating the algorithm's capability to navigate complex optimization landscapes. The experimental analysis involved comparing the GA with other optimization methods like PSO, ACO, and GA, which had shown the GA's effectiveness in reducing environmental impact and enhancing computational efficiency, thereby underlining its utility in advancing SM practices.

The paper is structured as follows: Section 2 presents the literature review, Section 3 presents the background for the work, Section 4 presents the methodology, Section 5 presents the evaluation of the work and Section 6 concludes the work.

II. LITERATURE REVIEW

The literature on the optimization of material selection, mainly related to the field of SM and design, has shown a significant interest in integrating computational intelligence and Machine Learning (ML) methodologies to handle the complexities associated with the corresponding material science.

[7] had proposed a model for material selection by introducing a novel Latent-Variable (LV) approach that was built within the Bayesian Optimization (BO) framework. They attempt to emphasize the BO's capability in material selection through the process of mapping qualitative design variables to numerical latent variables in Gaussian Process (GP) models. They applied their model in the environment, like optimizing the light absorption of quasi-random solar cells and the combinatorial search for optimal Hybrid Organic-Inorganic Perovskite (HOIP) designs. Through flexible parameterization and superior modelling accuracy, they provided an effective model for material selection that considered numerous qualitative factors of materials design.

[8] attempted to employ GA and ML-based predictive models to design polymers with extreme property measures. They combined different ML models together with the GA model and attempted to predict better material combinations. The idea behind their work was to examine the GA's potential in evolving polymer designs through the process of natural operations like crossover, mutation, and selection. Through experiments, they have generated chemically unique polymers with high thermal and electrical performance metrics.

[9-10] have both reviewed the role of ML in material selection in their respective work to demonstrate ML's potential to revolutionize against the traditional *trial-and-error* methodologies. These studies have been conducted through surveys and have highlighted the advantages of ML models' ability to enhance property prediction, material discovery, and the inverse design process. This enhanced processability adds an edge to the ML model's efficiency in advancing the material selection process.

[11] had mainly discussed the comprehensive perspective that is needed for more optimal materials design. This article mentioned the challenges and opportunities available for ML tools in the field of material science.

[12] had introduced a Material Generation Algorithm (MGA) model that was built with inspiration that arrived from material chemistry and chemical reactions. The MGA is a novel attempt to optimize engineering problems. Through various experiments, their work benchmarked the proposed MGA model against other Metaheuristic Algorithms (MA) [13-18]. Through various optimization problems, they demonstrated the proposed MGA's performance.

III. BACKGROUND

Introduction to Genetic Algorithm (GA)

GA are a subset of evolutionary algorithms inspired by the process of natural selection and concepts derived from Darwinian genetics. These algorithms are used to find optimized solutions to search and optimization problems through a process miming biological evolution. The following are the basic foundations of GA:

Population (P)

A set of candidate solutions to the problem. Each candidate solution is often referred to as a *"Chromosome"*. Mathematically, If P is a population, Then $P = \{C_1, C_2, \dots, C_n\}$ where C_i represents the i^{th} chromosome.

Chromosome (C)

A representation of a candidate solution. Chromosomes are typically expressed as strings of binary values, but they can also be represented by other structures depending on the problem domain. A chromosome C_i could be represented as $C_i = (g_1, g_2, \dots, g_m)$, where g_j represents the j^{th} gene in the chromosome.

Gene (g)

A part of a chromosome that determines a particular characteristic or parameter in the candidate solution. Genes are the basic units of data in GA.

Search Space

The search space, $'S'$, encompasses all potential solutions to the problem. Each solution is encoded as a chromosome, $'C'$, consisting of genes, g_i, where each gene represents a solution parameter. For a given problem, the search space is defined by $S = \{C_1, C_2, \dots, C_n\}$, where each $C_i = (g_1, g_2, \dots, g_m)$ represents a potential solution within the space.

Fitness Function

The fitness function, $f(C)$, quantitatively evaluates the suitability of a chromosome C as a solution to the problem. The function assigns a fitness score to each chromosome, influencing its likelihood of being selected for reproduction. The objective of a GA is to optimize this function, either by maximization or minimization, depending on the problem context.

GA manage a population of (n) individuals, each represented as a chromosome or solution, along with their corresponding fitness scores. Individuals with higher fitness scores are prioritized for reproduction over their counterparts. Those selected for mating combine their genetic material to produce offspring, potentially leading to superior solutions. Given the constant size of the population, space must be made for these new members. Consequently, some individuals are phased out and replaced by newcomers, facilitating the emergence of a new generation once the reproductive potential of the existing population is fully utilized. It is anticipated that, with each passing generation, more optimal solutions will emerge as less fit individuals are phased out.

With every new generation, there is, on average, an increase in *"Better Genes"* compared to the individuals from preceding generations, resulting in progressively improved *"Partial Solutions."* This iterative process continues until the offspring show negligible differences from those produced in prior cycles, indicating that the population has stabilized. At this point, the algorithm is considered to have converged, offering solutions for the given problem. Once the initial generation is created, the algorithm evolves the generation using the following operators:

Selection

A process by which chromosomes are chosen from the population for breeding based on their fitness. The selection process ensures that more fit chromosomes are more likely to be selected for reproduction.

Crossover

A genetic operator used to combine the genetic data of two parents to generate new offspring. It is a method of recombination. For example, given two chromosomes $C_a = (a_1, a_2, \dots, a_m)$ and $C_b = (b_1, b_2, \dots, b_m)$, a single-point crossover might produce an offspring $C_o = (a_1, a_2, \dots, a_k, b_{k+1}, \dots, b_m)$.

Mutation

A genetic operator used to maintain genetic diversity within the population by randomly altering one or more genes in a chromosome. For a chromosome $C_i = (g_1, g_2, \dots, g_m)$, a mutation might change g_j to g'_j.

The Process of GA Is Illustrated As follows

Initialization

Generate an initial population P_0 of n chromosomes randomly.

Evaluation

Compute the fitness $f(C_i)$ for each chromosome C_i in the population.

Selection
Select pairs of chromosomes from the current population to breed a new generation. Selection is often performed so that chromosomes with higher fitness are more likely to be selected.

Crossover and Mutation
Apply crossover and mutation operators to the selected chromosomes to produce offspring, which forms the next generation of solutions.

Replacement
Replace the current population with the new generation of chromosomes and return to step 2 unless a termination condition has been reached (*e.g.,* a sufficient fitness level or a maximum number of generations).

Sustainable Manufacturing
Sustainable manufacturing is a concept developed to achieve a minimal negative, energy environmentally friendly, economically viable, and socially acceptable. One of the critical attributes in developing SM is the process of proper material selection based on its attributes and functionalities. The materials decide the product's lifecycle, energy consumption (EC) in manufacturing, recycling ability, and the quality and efficiency of the produced product. This is why the focus was increased on material selection that could satisfy all the necessary criteria.

BPM
Within the diverse field of sustainable material science, the advent of BPM has emerged as a most sought-after material that could meet all the essential attributes of a material suited for SM. These materials are of such a kind that they offer the needed solution to the existing and most persistent problem of pollution, which is plastic waste. The BPMs are designed using technology that breaks down into natural substances like water, carbon dioxide, and biomass under specific conditions. By integrating those BPM into SM processes, the companies that are now handling plastic can employ BPM so that they can significantly reduce the environmental footprint of their products. The following **Fig 1** illustrates various applications for the usage of BPM.

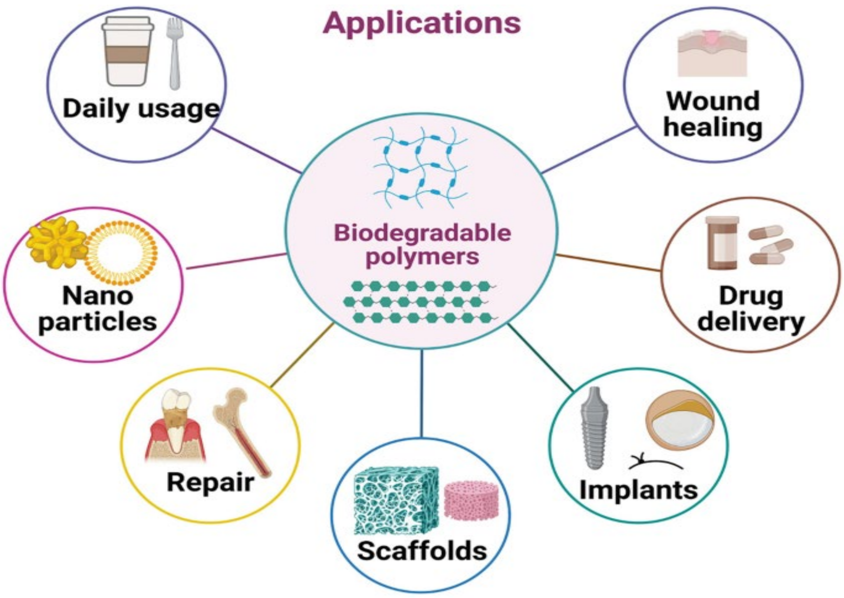

Fig 1. Applications of BPM.

Criteria for Selecting BPM
The selection of BPM is determined based on the following factors:
Environmental Impact (EI)
The environmental impact of BPMs is assessed throughout their product lifecycle, starting right from the process of raw material extraction and SM to end-of-life degradation. Factors like energy and resources consumed during production, the emissions generated, and the degradation time and conditions are also considered to measure the EI.

Performance Characteristics (PC)
The PC of BPMs determine their respective selection and application for specific domains. These characteristics include (i) mechanical strength, (ii) durability, flexibility, and (iii) resistance to heat and moisture.

Economic Viability (EV)
The decision-making process of one specific type of BPM is additionally determined by the cost for SM using that specific type. Because it decreases the total expense, the particularly feasible substance for business purposes must be selected for manufacturing. The EV also takes into consideration the cost of the raw materials, the cost of manufacturing processes, and any other expenses related to satisfying required regulations or environmentally friendly criteria.

Problem Definition
It must be accomplished to address the efficiency issue associated with selecting the most effective set of BPM for contextual SM approaches.

- Let $X = \{x_1, x_2, \ldots, x_n\}$ represent the set of BPM, where each x_i is a polymer characterized by a unique combination of features.
- Each polymer x_i is related to a set of features $A = \{a_1, a_2, \ldots, a_m\}$, such as degradation rate, mechanical strength, and cost, which define its appropriateness for sustainable work.

This purpose is subject to optimization and is expressed as follows: EQU (1).

$$F(X) = w_1 \cdot E(X) + w_2 \cdot P(X) - w_3 \cdot \text{Cost}\,(X) \tag{1}$$

where:

- $F(X)$ is the objective function,
- $E(X)$ quantifies the environmental impact of the polymer selection $'X'$, aiming for minimization,
- $P(X)$ represents the performance score, which we seek to maximize,
- $\text{Cost}\,(X)$ is the economic cost associated with the polymer selection, which should be minimized,
- w_1, w_2, and w_3 weights reflect the relative position of ecological impact, performance, and cost.

The challenge is to find the set of polymers $'X^{*\prime}$ that optimizes (X), EQU (2).

$$X^* = \text{Arg } \underset{X}{\text{Min}} F(X) \tag{2}$$

to minimize costs and environmental impact.

Search Space Definition
The search space $'S'$ is defined by the set of all possible combinations of polymers and their attributes that could potentially form a solution, EQU (3).

$$S = X_1 \times X_2 \times \ldots \times X_n \tag{3}$$

where $X_1, X_2, \ldots, X_n$ represent the ranges of possible values for each attribute across all considered polymers. The dimensionality of the search space is determined by the number of attributes $'m'$ considered for each polymer, making $'S'$ a multi-dimensional space that the GA navigates to find $'X^{*\prime}$.

IV. METHODOLOGY

Encoding BPM Selections into Chromosomes for GA Optimization
The encoding strategy involves the process of integrating the binary and real-valued representations to the features of BPMs effectively:

Chromosome (C_i)
Each chromosome in GA corresponds to a potential polymer selection, which is represented as an array of genes $C_i = [g_1, g_2, \ldots, g_m]$, where m is the total number of genes. Each gene encodes an attribute of the polymer; that way, the entire chromosome represents all the relevant properties that are needed for assessment.

Gene Representation
Binary Encoding for Discrete Attributes
Binary encoding is employed for discrete attributes in BPM, such as the polymer type. Each gene g_j within this category is a binary digit (0 or 1), where each bit position represents a different polymer type or characteristic.

Real-Valued Encoding for Continuous Attributes
Continuous attributes, including the degradation rate and mechanical properties like tensile strength and elasticity, are encoded as real numbers. The attribute selection for the GA optimization involves the following:

Type of Polymer (T)
The type of biodegradable polymer is encoded using binary digits (b). Each bit in a segment of the chromosome, $T = [b_1, b_2, \dots, b_k]$, represents a different type of biodegradable polymer. Here, k is the number of polymer types considered.

Degradation Rate (D)
The degradation rate reflecting how quickly a polymer degrades under environmental conditions. This attribute is encoded as a real-valued gene, D, within the chromosome.

Mechanical Properties (M)
Key mechanical properties, including tensile strength (M_{ts}) and elasticity (M_e), are encoded as real numbers. These properties are crucial for assessing the material's performance and are represented as $M = [M_{ts}, M_e]$ within the chromosome.

Economic Cost (C)
The economic viability of using a particular polymer type is encoded as a real-valued gene, C, reflecting the cost associated with production, processing, and other related expenses.

In applying this encoding scheme within the GA model, each chromosome C_i represents a potential solution, *i.e.,* a specific selection of biodegradable polymers, and is structured as follows: EQU (4).

$$C_i = [T, D, M, C] \tag{4}$$

where:
- C_i is the i^{th} chromosome,
- T encodes the type(s) of biodegradable polymer included,
- D represents the degradation rate,
- M encodes mechanical properties and
- C denotes the economic cost.

Fitness Function Implementation
The fitness function, $F(C_i)$, for each chromosome C_i in the population directly reflects the optimization goals of minimizing environmental impact and cost while maximizing material performance. The function is formulated as follows, integrating the previously defined attributes and their notations, EQU (5).

$$F(C_i) = w_1 \cdot E(C_i) + w_2 \cdot P(C_i) - w_3 \cdot \text{Cost}\,(C_i) \tag{5}$$

where:
- $F(C_i)$ is the fitness score of chromosomes C_i,
- $E(C_i)$ quantifies the environmental impact of the polymer selection encoded by C_i,
- $P(C_i)$ represents the performance score, incorporating mechanical properties and degradation rate,
- Cost (C_i) denotes the economic cost associated with the selection, w_1, w_2, and w_3 are the weights reflecting the relative importance of each criterion.

Environmental Impact $\big(E(C_i)\big)$
The Environmental Impact $E(C_i)$ of a polymer, selection can be quantified by considering factors such as the degradation rate and the energy required for production. An EQU (6) to represent this component might look like the following:

$$E(C_i) = \alpha \cdot DEG(C_i) + \beta \cdot ENR(C_i) \tag{6}$$

where:
- $DEG(C_i)$ is the degradation rate of the polymer selection, with higher rates generally preferred to ensure rapid decomposition.
- $ENR(C_i)$ represents the energy required for producing the selected polymers, with lower energy consumption preferable.
- α and β are weighting factors that reflect the relative importance of degradation rate and energy consumption in the overall environmental impact assessment.

Performance Score $\big(P(C_i)\big)$
The Performance Score $P(C_i)$ evaluates the suitability of the polymer selection in meeting mechanical and functional specifications. This can be expressed as a weighted sum of relevant performance attributes, EQU (7).

$$P(C_i) = \gamma \cdot TENS(C_i) + \delta \cdot ELAS\,(C_i) \tag{7}$$

where:

- $TENS(C_i)$ Measures the tensile strength of the polymer selection, indicative of its mechanical robustness.
- ELAS (C_i) Assesses the elasticity of the polymer selection, reflecting its flexibility and durability under stress.
- γ and δ are weights assigned to the tensile strength and elasticity, respectively, indicating their importance in the overall performance evaluation.

Economic Cost $\left(Cost\ (C_i)\right)$

The Economic Cost Cost (C_i) Associated with a polymer selection, raw material costs, production, and processing expenses are covered. This can be modelled as EQU (8).

$$\text{Cost}\,(C_i) = \theta \cdot MAT(C_i) + \lambda \cdot \text{PROC}\,(C_i) \tag{8}$$

where:

- $MAT(C_i)$ represents the cost of raw materials for the polymer selection.
- PROC (C_i) Includes the costs associated with processing and producing the selected polymers.
- θ and λ are weighting factors that balance the impact of raw material costs and processing expenses on the total economic cost.

Customizing Genetic Operators

These operators must be tailored to effectively navigate the unique landscape of material properties and sustainability criteria. This customization enhances the GA's ability to identify optimal polymer combinations by ensuring that genetic diversity is maintained and that the search space is thoroughly explored.

Selection Operators

The selection operator's role is to choose individuals from the population for reproduction, prioritizing those with higher fitness scores to ensure the propagation of advantageous traits. For the BPM selection problem:

Tournament Selection is employed due to its balance between preserving genetic diversity and ensuring the advancement of fit individuals. In this method, a set number of individuals are randomly selected from the population to participate in a "tournament," the individual with the highest fitness within this group is chosen for reproduction. This process is repeated until the desired number of individuals is selected for the next generation.

Given a tournament size of k, the selection process for one individual can be expressed as follows:

- Randomly select k individuals from the population.
- Compare the fitness scores, $F(C_i)$, of the selected individuals.
- The individual with the highest fitness score wins the tournament and is selected.

The mathematical expression for selecting one individual through Tournament Selection can be represented as EQU (9).

$$\text{Select}\,(C_i) = \max\{F(C_{i1}), F(C_{i2}), \dots, F(C_{ik})\} \tag{9}$$

where $C_{i1}, C_{i2}, \dots, C_{ik}$ are the chromosomes of the individuals participating in the tournament, and $F(C_i)$ is the fitness function evaluating each individual's suitability.

Customizing Crossover Operators

Crossover, or recombination, combines the genetic data of two parents to generate offspring, encouraging the exploration of new regions in the search space. To explore new combinations of polymer properties effectively, a Uniform Crossover strategy is implemented for the recombination of parental chromosomes:

Uniform Crossover Strategy

For two parent chromosomes C_p and C_q, each gene g_j in the offspring chromosome C_o is chosen randomly from the corresponding genes in C_p and C_q with equal probability. This approach ensures equitable contribution from both parents across the entire gene set, suitable for the mixed nature of binary and real-valued encoded attributes, EQU (10).

$$C_o[j] = \begin{cases} C_p[j] & \text{With Probability } 0.5 \\ C_q[j] & \text{With Probability } 0.5 \end{cases} \tag{10}$$

Customizing Mutation Operators

Mutation introduces random alterations in the chromosome, aiding in exploring the search space and preventing the GA from becoming trapped in local optima. Considering the composite encoding of chromosomes, a Hybrid Mutation strategy is adopted, differentiating between binary and real-valued genes:

Bit-Flip Mutation for Binary Genes

For binary-encoded segments representing discrete polymer types or characteristics, the bit-flip mutation is applied. If g_j is a binary gene, its state is flipped with a mutation probability p_m, EQU (11).

$$p_m = \begin{cases} 1 - g_j & \text{If rand () } < p_m \\ g_j & \text{Otherwise} \end{cases} \tag{11}$$

Random Mutation for Real-Valued Genes

For real-valued genes encoding continuous attributes like degradation rate or mechanical properties, a random mutation is performed by adding a small, randomly selected delta, $'\Delta$' within predefined limits, ensuring the exploration of nearby solution space, EQU (12).

$$g_j' = g_j + \Delta, \tag{12}$$

where Δ is a random value within the attribute's range

The proposed algorithm using GA for the BMP selection is presented below:

Algorithm: GA for Optimized Selection of BPM

Inputs:

- N : Number of individuals in the population.
- $G_{\max}$: Maximum number of generations.
- p_c : Probability of crossover.
- p_m : Probability of mutation.
- k : Tournament size for selection.
- $\{T, D, M, C\}$: Set of BPM attributes
- Weights w_1, w_2, w_3: weights for environmental impact, performance, and cost in the fitness function.

Process:

1 **Initialize Population:** Generate an initial population of N individuals randomly. Each individual represents a set of BPM attributes encoded as chromosomes.

2 **Evaluate Fitness: For Each** individual in the population, calculate their fitness based on the EQU (13):

$$F(C_i) = w_1 \cdot E(C_i) + w_2 \cdot P(C_i) - w_3 \cdot \text{Cost }(C_i) \tag{13}$$

where E, P, and Cost are the environmental impact, performance score, and economic cost of the BPM, respectively.

3 **For Each** generation in 1 to $G_{\max}$ **Do**:

- **Selection:**
  - **For** i from 1 to N **Do**:
    - Conduct k-tournament selection to choose parents.

- **Crossover:**
  - **For Each** pair of parents **Do:**
    - **If** random () $< p_c$ **Then,** a uniform crossover will be performed to produce offspring.

- **Mutation:**
  - **For Each** offspring, **Do:**
    - **For Each** gene in offspring, **Do:**
      - **If** random () $< p_m$ **Then:**
        - **If** the gene is binary (*e.g.,* Type):
          - Apply bit-flip mutation.
        - **Else If** the gene is real-valued (*e.g.,* Degradation Rate, Mechanical Properties, Cost):
          - Apply random perturbation within range.

- **Evaluate the Fitness of New Offspring:** Calculate the fitness of each new offspring using the fitness function.
- **Replacement:** Integrate offspring into the population, replacing the least fit individuals.
- **Check Stopping Criterion:** Exit the loop if a predefined stopping criterion is met.

4 **Identify Optimal Selection:** At the end of $G_{\max}$ generations, identify the individual with the best fitness score as the optimal set of biodegradable polymers, X^*.

5 **Output:** Return the optimal set X^* and its fitness score, detailing the selected biodegradable polymers' attributes and their alignment with sustainability, performance, and cost objectives.

V. EXPERIMENT ANALYSIS

A packaging manufacturing company located in Shenzhen, China, is seeking to transition to eco-friendly materials to reduce environmental impact without compromising product quality or significantly increasing costs. The company aims to utilize BPM for its new range of packaging materials. This case study aims to apply the GA to select the optimal combination of BPM that balances environmental friendliness, material performance, and cost-effectiveness.

Data Collection and Preparation

The data collection process involves details about different polymers that are sourced from academic literature, industrial input and product catalogues. Each polymer is characterized by a set of attributes (**Table 1**): type (T), degradation rate (D), mechanical properties (M), and cost (C).

Type (T)

This attribute relates to the chemical composition of BPM, which includes PLA (Polylactic Acid), PHA (Polyhydroxyalkanoates), PBAT (Polybutylene Adipate Terephthalate), and others.

Degradation Rate (D)

Measures the rate of how quickly a polymer can degrade into environmentally benign substances.

Mechanical Properties (M)

This includes tensile strength, elasticity, and durability under various conditions.

Cost (C)

Representing the economic viability of each polymer option, it includes the raw material expenses, processing and manufacturing costs.

Table 1. Polymer Attributes

Polymer Type (T)	Origin	Degradation Rate (D)	Mechanical Properties (M)	Cost (C)
PLA (Polylactic Acid)	Synthetic	6-12 months (Industrial Composting)	Tensile Strength: 45-60 MPa, Elasticity: Moderate	Medium
PHA (Polyhydroxyalkanoates)	Natural	9-18 months (Soil Burial)	Tensile Strength: 35-45 MPa, Elasticity: High	High
PBAT (Polybutylene Adipate Terephthalate)	Synthetic	3-6 months (Soil)	Tensile Strength: 25-35 MPa, Elasticity: Very High	Medium-High
PBS (Polybutylene Succinate)	Synthetic	6-9 months (Industrial Composting)	Tensile Strength: 40-50 MPa, Elasticity: Moderate	Medium

Preparation

To prepare the data for the GA, the following steps were undertaken:

Normalization

Attributes were normalized to ensure comparability and to balance their influence in the optimization process. For instance, mechanical properties and degradation rates were scaled to a typical range, facilitating a uniform assessment of material performance and environmental impact.

Encoding

Each polymer's attributes were encoded into a format suitable for GA processing. The type attribute was encoded using binary digits to represent the presence or absence of specific polymer categories. Continuous attributes, such as degradation rate and mechanical properties, were encoded as real numbers within their respective ranges.

Data Cleaning

The incomplete and inconsistent entries are addressed by the data cleaning processes.

Preliminary Screening

An initial screening was conducted to exclude polymers that did not meet basic environmental or performance thresholds, such as those with prolonged degradation rates and inadequate mechanical strength for packaging applications.
The following **Table 2** presents the description of the collected dataset. The GA model was trained using parameters as shown in **Table 3.**

Table 2. Dataset Description

Attribute Description	Data Type	Value Range or Categories
Polymer Type (T)	Categorical	PLA, PHA, PBAT, PBS
Origin	Categorical	Natural, Synthetic, Hybrid
Degradation Rate (D)	Continuous	*e.g.,* 3-18 months
Tensile Strength (Part of M)	Continuous	*e.g.,* 25-60 MPa
Elasticity (Part of M)	Qualitative	Low, Moderate, High, Very High
Cost (C)	Continuous	*e.g.,* \$0.5 - \$5 per kilogram

Table 3. Hyperparameters for GA

Parameter	Example Value
Population Size (N)	100
Number of Generations (G_{max})	50
Crossover Probability (P_c)	0.8
Mutation Probability (P_m)	0.1
Tournament Size (k)	5

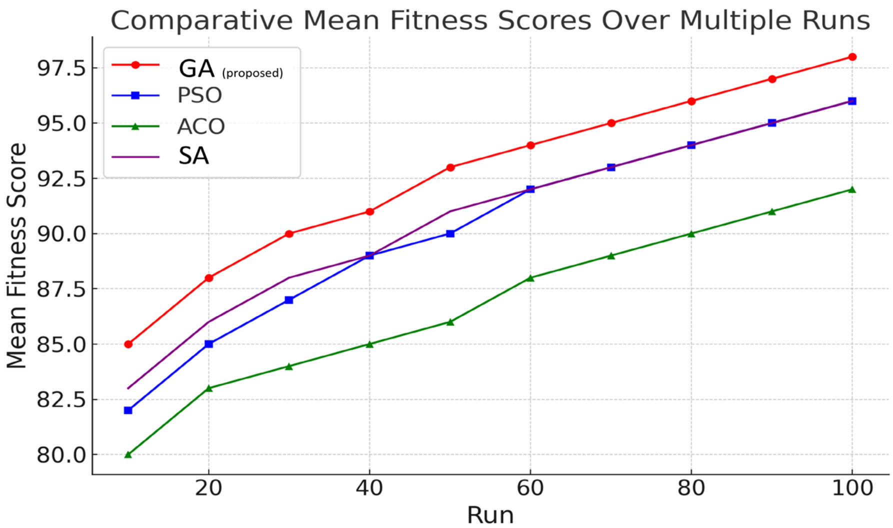

Fig 2. Mean Fitness score.

The graph in **Fig 2** shows the mean fitness score of compared models over multiple runs. The GA proposed in this work starts at a score of 85 and reaches 97.5 at run 100. Both the start and end scores of the GA model are higher than those of other models, such as PSO, ACO, and SA. The overall performance at each run is consistent with each experiment run compared to the other models. The subsequent analysis is the environmental impact assessment of each model against multiple runs, as shown in **Fig 3**. The analysis shows that the models performing lesser impact scores are considered more than the others. From the results, it can be seen that the GA model has a lower impact score than the other models. The GA achieves lower scores of 25. The SA shows a slightly higher impact score of 27. In contrast, the ACO scored the highest at 30. The GA had the lowest score of all models, suggesting its adaptability in such environments.

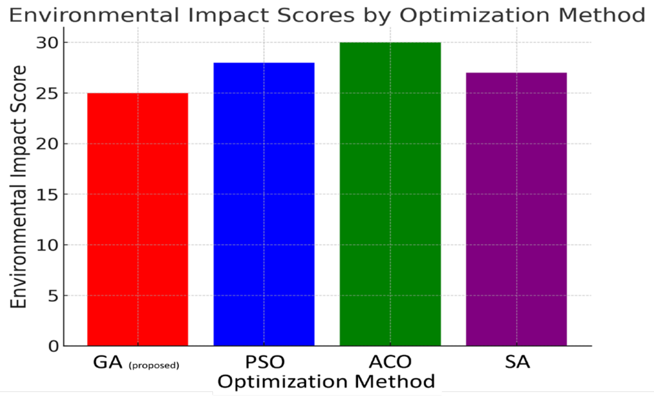

Fig 3. Environment Impact Assessment.

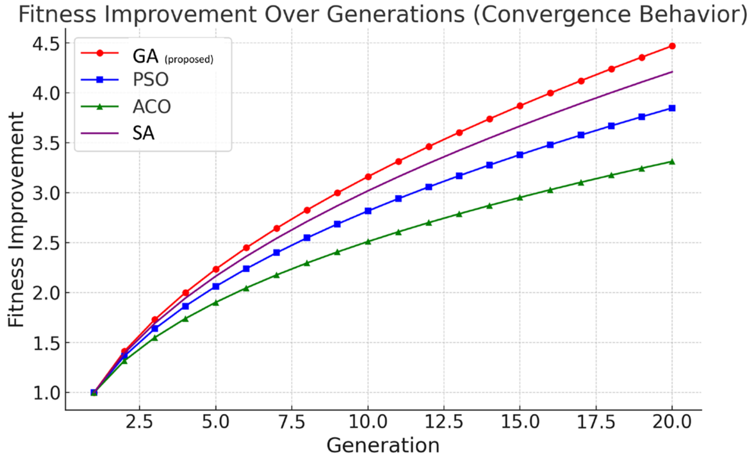

Fig 4. Fitness Improvement Assessment.

Fig 4 shows the fitness improvement of different optimization algorithms over successive generations. The GA displayed substantial fitness improvement for each generation, starting around 1 and progressing to 4.5 by the 20^{th} generation. The model displayed better convergence as the generations progressed. Following the GA, the SA model also shows better convergence than the other models, such as PSO+ACO. Considering all the models, the GA model showed better convergence than the other models.

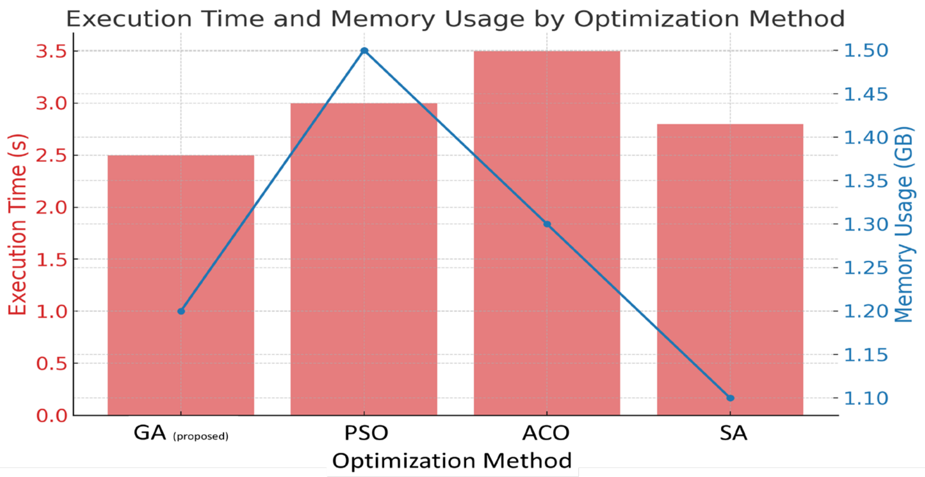

Fig 5. Execution Time (ET) vs Memory Usage (MU).

Most of the examined models' ET and MU are displayed in **Fig 5**. When evaluating the performance of the two approaches, the GA approach consistently emerges as the best for MU and ET. The SA model was second in ET and first in MU, contrasting with the GA, which is intriguing. When contrasted with all the additional models, the ACO exhibits the highest ET, and the PSO uses the most considerable memory. Based on these results, the GA is superior to all other versatile approaches in the context of material selection.

VI. CONCLUSION AND FUTURE WORK

The research investigation found that Genetic Algorithms (GA) have enormous potential for optimizing material selection, focusing on environmentally conscious production. In order to deal with the challenges of environmentally friendly polymer selection, this work recommends including the GA technique. Factors for material selection comprised the effects on the environment, how they perform, and cost, among others. The application used a case study on a product manufacturer's switch to using biodegradable polymer materials for sustainable manufacturing. The research study examined the framework of others, like PSO, ACO, and GA, and found that the GA model is more appropriate for application in the materials field for effective substance decision-making, considering a selection of evaluation parameters.

Further, this research suggests GA and other algorithmic approaches can be used in several contexts that are sustainable industries.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests

There are no competing interests.

References

[1]. M. Abubakr, A. T. Abbas, I. Tomaz, M. S. Soliman, M. Luqman, and H. Hegab, “Sustainable and Smart Manufacturing: An Integrated Approach,” Sustainability, vol. 12, no. 6, p. 2280, Mar. 2020, doi: 10.3390/su12062280.

[2]. C. Enyoghasi and F. Badurdeen, “Industry 4.0 for sustainable manufacturing: Opportunities at the product, process, and system levels,” Resources, Conservation and Recycling, vol. 166, p. 105362, Mar. 2021, doi: 10.1016/j.resconrec.2020.105362.

[3]. C. Maraveas, “Production of Sustainable and Biodegradable Polymers from Agricultural Waste,” Polymers, vol. 12, no. 5, p. 1127, May 2020, doi: 10.3390/polym12051127.

[4]. S. Gopalakrishnan, N. W. Hartman, and M. D. Sangid, “Model-Based Feature Information Network (MFIN): A Digital Twin Framework to Integrate Location-Specific Material Behavior Within Component Design, Manufacturing, and Performance Analysis,” Integrating Materials and Manufacturing Innovation, vol. 9, no. 4, pp. 394–409, Nov. 2020, doi: 10.1007/s40192-020-00190-4.

[5]. E. S. Hosseini, S. Dervin, P. Ganguly, and R. Dahiya, “Biodegradable Materials for Sustainable Health Monitoring Devices,” ACS Applied Bio Materials, vol. 4, no. 1, pp. 163–194, Dec. 2020, doi: 10.1021/acsabm.0c01139.

[6]. B. Alhijawi and A. Awajan, “Genetic algorithms: theory, genetic operators, solutions, and applications,” Evolutionary Intelligence, vol. 17, no. 3, pp. 1245–1256, Feb. 2023, doi: 10.1007/s12065-023-00822-6.

[7]. Y. Zhang, D. W. Apley, and W. Chen, “Bayesian Optimization for Materials Design with Mixed Quantitative and Qualitative Variables,” Scientific Reports, vol. 10, no. 1, Mar. 2020, doi: 10.1038/s41598-020-60652-9.

[8]. C. Kim, R. Batra, L. Chen, H. Tran, and R. Ramprasad, “Polymer design using genetic algorithm and machine learning,” Computational Materials Science, vol. 186, p. 110067, Jan. 2021, doi: 10.1016/j.commatsci.2020.110067.

[9]. J. Cai, X. Chu, K. Xu, H. Li, and J. Wei, “Machine learning-driven new material discovery,” Nanoscale Advances, vol. 2, no. 8, pp. 3115–3130, 2020, doi: 10.1039/d0na00388c.

[10]. S. M. Moosavi, K. M. Jablonka, and B. Smit, “The Role of Machine Learning in the Understanding and Design of Materials,” Journal of the American Chemical Society, vol. 142, no. 48, pp. 20273–20287, Nov. 2020, doi: 10.1021/jacs.0c09105.

[11]. S. Talatahari, M. Azizi, and A. H. Gandomi, “Material Generation Algorithm: A Novel Metaheuristic Algorithm for Optimization of Engineering Problems,” Processes, vol. 9, no. 5, p. 859, May 2021, doi: 10.3390/pr9050859.

[12]. S. O. Ongbali, S. A. Afolalu, E. Y. Salawu and S. A. Omotehinse, "Review of Project Monitoring and Evaluation Technique as Index for Sustainable Manufacturing Performance," 2023 International Conference on Science, Engineering and Business for Sustainable Development Goals (SEB-SDG), Omu-Aran, Nigeria, 2023, pp. 1-5, doi: 10.1109/SEB-SDG57117.2023.10124516.

[13]. N. Ganjavi and H. Fazlollahtabar, "Integrated Sustainable Production Value Measurement Model Based on Lean and Six Sigma in Industry 4.0 Context," in IEEE Transactions on Engineering Management, vol. 70, no. 6, pp. 2320-2333, June 2023, doi: 10.1109/TEM.2021.3078169.

[14]. M. S. K. Pheng and L. G. David, "Artificial Intelligence in Back-End Semiconductor Manufacturing: A Case Study," 2022 IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), Ballari, India, 2022, pp. 1-4, doi: 10.1109/ICDCECE53908.2022.9792976.

[15]. N. M. Durakbasa, G. Bas, D. Riepl, and J. M. Bauer, “An innovative educational concept of teleworking in the high precision metrology laboratory to develop a model of implementation in the advanced manufacturing industry,” Proceedings of 2015 12th International Conference on Remote Engineering and Virtual Instrumentation (REV), Feb. 2015, doi: 10.1109/rev.2015.7087288.

[16]. C. H. Yang, “Development of intelligent building management system evaluation and selection for smart factory: An integrated MCDM approach,” 2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Dec. 2017, doi: 10.1109/ieem.2017.8290144.

[17]. B. B. Kanbur, S. Shen, Y. Zhou and F. Duan, "Neural network-integrated multiobjective optimization of the 3D-printed conformal cooling channels," 2020 5th International Conference on Smart and Sustainable Technologies (SpliTech), Split, Croatia, 2020, pp. 1-6, doi: 10.23919/SpliTech49282.2020.9243730.

[18]. R. Poler et al., "An IoT-based Reliable Industrial Data Services for Manufacturing Quality Control," 2021 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), Cardiff, United Kingdom, 2021, pp. 1-8, doi: 10.1109/ ICE/ITMC52061.2021. 9570203.