A Genetic Artificial Bee Colony Algorithm for Investigating Job Creation and Economic Enhancement in Medical Waste Recycling

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***Abstract*—The effective management of end-of-life products, whether through recycling or incineration for electricity generation, holds pivotal significance amidst escalating concerns over economic, environmental, and social ramifications. While the economic and environmental dimensions often receive primary focus, the social aspect remains comparatively neglected within sustainability discourse. This paper undertakes a comprehensive exploration of the positive social impacts engendered by medical waste recycling, with a specific focus on job creation and economic value enhancement. The principal aim of this research is to highlight the social benefits derived from medical waste recycling, elucidating its role in fostering employment opportunities, and augmenting economic prosperity. By employing a Genetic Artificial Bee Colony algorithm, this study addresses two mathematical problems pertinent to optimizing recycling processes, thereby contributing to the advancement of sustainable waste management practices. Additionally, the proposed algorithm exhibits superior performance, highlighting its potential in addressing sustainability challenges. Ultimately, integrating the social dimension into end-of-life product management discussions can lead to a more comprehensive approach to sustainability, balancing environmental preservation with socio-economic progress.**

Keywords*—*Medical waste recycling; social impacts; genetic artificial bee colony algorithm; job creation; economic value

I. Introduction

The growth of the population and their increasing demand for consumable products necessitate a concerted effort to reduce the amount of waste generated by these products after use, the management of products extends far beyond their initial creation and use. The footprint left by this waste has become a critical concern, urging a transition from the traditional "cradle-to-grave" model, to the more encompassing and sustainable "cradle to cradle". The increase in waste in landfill sites becomes a crucial challenge for decision-makers, researchers, and consumers, considering the dangers effects that can be caused by the poor management of these wastes, whether at the economic, environmental, or social dimensions. Addressing these three challenges in the design of a closed-loop supply chain (CLSC) forms the three pillars of sustainability [1]. The complexity of the intersection between environmental, economic, and social considerations finds its explanation in the model of designing a CLSC. This represents a systematic departure from the "cradle to grave" model, emphasizing a circular economy, environmental concerns, and social indicators.

Recently, in the discourse on sustainable development, one of the sectors that attracts the attention of researchers and decision-makers is the healthcare sector. This sector is subject to increased scrutiny, especially after the Covid-19 pandemic, wars, and natural disasters that have generated substantial amount of medical waste in recent years. According to the World Health Organization report [2], the COVID-19 pandemic generated tens of thousands of tons of medical waste between March 2020 and November 2021. These wastes are disposed of in landfill sites without any treatment. This situation highlights the importance of adopting a strategy to implement the principles of reverse logistics in traditional supply chain management and integrating environmental concerns and social indicators.

It is evident that in recent times, the focus of decision-makers and researchers has pivoted towards the environmental impact resulting from supply chain. While there is an increasing recognition of the importance of reducing the environmental footprint to attain the second dimension of a sustainable CLSC network, there remains a noticeable gap in the existing literature concerning the third dimension of sustainability, namely, social impacts[3]. This study aims to highlight the importance of integrating social indicators into sustainable CLSD. Recycling medical waste can have several positive social impacts contributing to the well-being of societies and individuals, including the community, workplace safety, education and awareness, and job creation. This study focuses on two social indicators: the first is job creation, which plays a significant role in reducing unemployment rates, and the second is balancing economic development.

The rest of this article is outlined as follows: Section II provides a review of the literature. In Section III, we delve into a detailed description of the problem and the corresponding mathematical model. Section IV introduces the Genetic Artificial Bee Colony (GABC) algorithm proposed in this study. The practical implementation of GABC and a comparative analysis between the results obtained by GABC and the original ABC are presented in Section V. Finally, Section VI offers concluding remarks.

II. Literature Reviews

For decades, the main objective of supply chains has been the maximization of profit or the minimization of costs throughout the network. This goal has been the focus of many research works and studies [4], [5], [6], [7], [8]. The efforts made by researchers to increase the profit of the logistics chain undeniably contributed to enhancing its efficiency and profitability.

In order to reduce total supply chain operating costs, A bi-objective optimization approach is presented by [9], which aims to minimize total expenditures and decrease cycle time delay overall. They use a solution strategy that combines the dual simplex method, the constraint method, and scatter search when taking discrete facility capacity alternatives into consideration. A trade-off between the two goals is shown by computational analyses, which show that decreasing cycle time produces a decentralized network structure while optimizing for cost produces a centralized network structure. The author in [10] present a novel model for designing a reliable network in a closed-loop supply chain, minimizing total and post-failure transportation costs under uncertainty. Their solution approach, combining robust optimization, queuing theory, and fuzzy multi-objective programming, proves effective in addressing uncertainty and optimizing facility design. The author in [11] provide a mixed-integer linear programming model for a closed-loop supply chain network that uses stochastic programming to minimize overall costs and account for uncertainties. To solve the complex problem of creating cost-effective closed-loop supply chains, [12] provide a novel approach that uses a deterministic multi-product, multi-echelon, multi-period model. The author in [13] proposes a novel Genetic Artificial Bee Colony (GABC) algorithm for optimizing closed-loop supply chain networks, addressing uncertainties in demand, and returned product quantities. Their GABC algorithm surpasses standard Artificial Bee Colony (ABC) and Genetic Algorithm (GA) methods in minimizing total network cost across diverse scenarios. The author in [14] uses an integer-programming approach to address a two-stage supply chain distribution-allocation problem. They proposed heuristic, based on Ant Colony Optimization, exhibits computational efficiency, and produces solutions in a fair amount of time with an average deviation from optimal solutions of about 10%. The author in [15] propose a mobile Waste Heat Recovery (WHR) supply chain, minimizing distribution costs compared to traditional WHR. Their optimization model, integrating life cycle assessment, ensures energy supply stability and cost savings, presenting an efficient alternative to conventional WHR and fossil fuel heating, especially under stochastic demand conditions. The author in [16] explores the economic advantages of new product formulations, specifically through concentration, in formulated product supply chain networks. They reduce overall costs by optimizing facility locations, capacities, and production planning through the use of mixed-integer linear programming, which has major advantages in a supply chain for fast-moving consumer goods.

Recently, the challenge of implementing a sustainable CLSC that adheres to the three dimensions of sustainability has become a task facing the researchers and the decision-makers. It is noted that several studies are beginning to incorporate environmental and / or social impacts as additional objectives in their multi-objective CLSC. The literature on the sustainable CLSC can be categorized into two primary groups: Economic and environmental dimensions in CLSC and sustainable CLSC.

A. *Economic and Environmental Dimensions in CLSC*

Over the past two decades, the challenge of environmental impacts generated by industries and end-of-life waste, leading to an increase in greenhouse gas (GHG) emissions and loss of natural resources, has become a major focus for researchers. The author in [17] introduce a conceptual framework for designing a sustainable food packaging and distribution network, comparing the environmental and economic impacts of reusable plastic containers (RPC) with traditional single-use options in the fresh food supply chain. Using life cycle assessment (LCA), the study evaluates the carbon footprint and explores sensitivity to key parameters, offering insights into the sustainability of packaging approaches in the food catering chain. The author in [18] presents a multi-objective model for the logistics of the gold industry that gives cost and CO2 emissions priority. Their work effectively addresses a case study of a 7-layer network using an ant colony optimization technique, demonstrating usefulness. The algorithm performs better when the parameters are set Taguchi-based, and the results highlight managerial insights for supply chain optimization. The author in [19] addresses environmental concerns by proposing a green supply chain model that optimizes transportation and waiting times for fleets in both forward and reverse logistics. The model aims to minimize environmental impacts and energy consumption through strategic determinations of loading, unloading, and production rates. The author in [20] explores how producing power from wood pellets might help achieve climate objectives. They focus on how supply chain costs can be reduced by using techno-economic analysis and a study of relevant research. The analysis highlights the impact of variables such as plant size on costs by revealing trade-offs in cost components across various supply chain configurations. [21]propose novel mathematical models for inventory management in reverse logistics systems, extending [22] model by considering different demands for newly produced and remanufactured products. The study also extends into sustainability, presenting a three-objective mathematical model and an algorithm to achieve Pareto solutions, addressing greenhouse gas emissions and energy consumption in production and remanufacturing processes. The author in [23] innovate a methodology for plastic footprint analysis at the enterprise and supply chain levels, focusing on a clothing industry case. Their study identifies key strategies, such as lightweight plastic promotion and increased use of recycled materials, offering practical solutions for substantial environmental benefits in reducing plastic impact.

B. *Social Dimension*

The concept of sustainability was introduced by [24] report, emphasizing the importance of integrating environmental and social concerns to ensure a viable future. Unfortunately, in the literature, the social dimension has rarely been addressed. The author in [25] aims to improve reverse logistics decision-making by integrating economic, environmental, and social objectives. Using a recyclable waste collection system as a case study, they model the problem as a multi-objective, multi-depot periodic vehicle routing challenge, proposing a compromise solution for a sustainable reverse logistics plan that considers trade-offs and achieves balance. The author in [26] introduces a multi-objective possibilistic programming model for designing a sustainable medical supply chain network under uncertainty, addressing conflicting economic, environmental, and social objectives. The model employs effective social and environmental life cycle assessment methods, and an accelerated Benders decomposition algorithm is introduced to handle computational complexity, demonstrated through a medical industrial case study. The authors in [27] have introduced an innovative sustainable closed-loop location-routing-inventory model. This model considers economic, environmental, and social impacts, particularly in the context of mixed uncertainty. The author in [28] address the need for supply chain designs considering environmental, social, and economic objectives, specifically focusing on sustainable closed-loop supply chain networks for recycled tires. They develop a multi-objective mixed-integer linear programming model to optimize total cost, environmental impacts, and social factors. To efficiently handle large-scale networks, four new hybrid metaheuristic algorithms are introduced and demonstrated to be effective through extensive computational experiments and analyses. The author in [29] develops a multi-objective linear mathematical model to optimize a steel sustainable closed-loop supply chain, addressing uncertainties and applying fuzzy goal programming. Validated through a real case study in an active steel supply chain in Iran, the model aims to optimize total profit, energy and water consumption, CO2 emissions, job opportunities, and lost working days. Results highlight the significant environmental benefits achievable even with a minor profit decrease, providing essential managerial insights for industry leaders navigating the balance between profits and environmental/social considerations. The author in [30] highlights the impact of decisions related to facility locations and industrial activities on initial pollution levels and unemployment rates in various regions. Through numerical experiments, the research demonstrates that intentional objectives focused on reducing environmental and social inequities lead to a decrease in disparities among regions. The paper concludes by providing managerial insights and suggesting future research directions within the context of supply chain networks and sustainable development.

Due to the diverse nature of social responsibility aspects, integrating all of them into the design of a sustainable closed-loop supply chain would lead to a non-optimal network. Our primary objective in this paper is to maximize positive social indicators in recycling three types of medical waste: glass, plastic, and steel. To achieve this, we propose a programming model with two objective functions that aims to maximize job creation and balance economic development. The study introduces a Genetic Artificial Bee Colony (GABC) algorithm, and its performance is compared with the original Artificial Bee Colony algorithm. This work builds upon our previous research [31], which focuses on minimizing the total cost of reverse logistics and reducing CO2 emissions in the network.

III. Problem Modeling

This model aims to develop a programming model for two objective functions to maximize job opportunities creation and balance economic value within a reverse supply chain network. The network encompasses hospitals, collecting centers, recyclers, and disposal centers. Fig. 1 illustrates the network schematic, emphasizing the reverse logistics aspect. The medical waste generated by the hospitals is shipped to collecting centers where the waste is disinfected and sorted. In this study, three types of waste are addressed: plastic (Polyethylene (PET), Polypropylene (PP)), glass (clear or white glass and brown glass), and stainless steel. The non-recyclable waste is transported to disposal centers, while the remaining medical waste is directed to recycling centers where it is processed and recycled to be used as new products. The unrecovered waste is shipped to the disposal center for safe landfill.

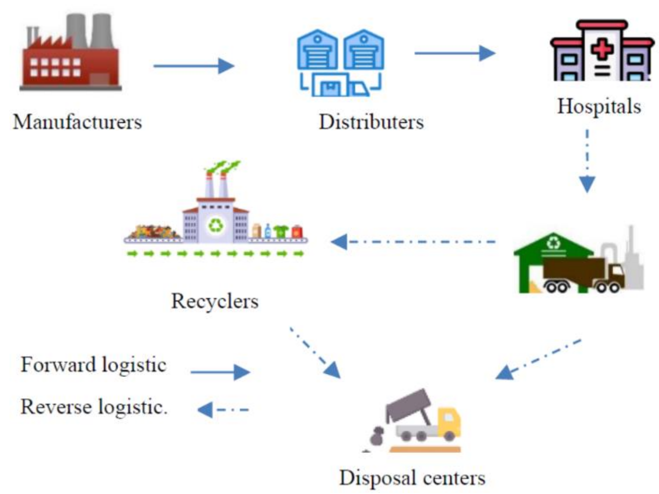

Fig. 1. Medical product for forward / reverse logistics network.

A. Assumptions

To formulate our model, we have based our analysis on the following assumptions and simplifications:

- There are no exchanges of products among facilities at the same level.
- The locations for the opening of recyclers and collecting centers are predetermined.
- The capability of each facility is constrained.
- The quality of recycled products and manufactured products is the same.
- The unrecovered waste is transported to a disposal center for safe landfilling.

B. Notation

- Indices

l : Index of hospitals, $l \in \{1, \dots, L\}$.

n : Index of collecting centers, $n \in \{1, \dots, N\}$.

m : Index of recyclers, $m \in \{1, \dots, M\}$.

o : Index of disposal centers, $o \in \{1, \dots, O\}$.

k : Index of plastic waste, $k \in \{1, \dots, K\}$.

r : Index of glass waste, $r \in \{1, \dots, R\}$.

v : Index of plastic waste, $v \in \{1, \dots, V\}$.

- Parameters

DJ_{km} : Number of fixed job opportunities created by establishing plastic recycler m.

DJ_{rm} : Number of fixed job opportunities created by establishing glass recycler m.

DJ_{vm} : Number of fixed job opportunities created by establishing steel recycler m.

DJ_n : Number of fixed job opportunities created by establishing collecting center n.

IDJ_n : Number of variable job opportunities created at collecting center c (depends on amount of waste and capacity of collecting center).

IDJ_{km} : Number of variable job opportunities created at plastic recycler m.

IDJ_{rm} : Number of variable job opportunities created at glass recycler m.

IDJ_{vm}: Number of variable job opportunities created at steel recycler m.

μ_n : Unemployment rate at collecting center n.

μ_{km} : Unemployment rate at plastic recycling center m.

μ_{rm} : Unemployment rate at glass recycling center m.

μ_{vm} : Unemployment rate at steel recycling center m.

V_{km} : Economic Value of recycling waste at plastic recycler m.

V_{rm} : Economic Value of recycling waste at glass recycler m.

V_{vm} : Economic Value of recycling waste at steel recycler m.

V_n : Economic Value at collecting center n.

rd_{km} : Regional development at plastic recycler m.

rd_{rm} : Regional development at glass recycler m.

rd_{vm} : Regional development at steel recycler m.

rd_n : Regional development at collecting center n.

δ_k : The percentage of non-recyclable plastic waste being transported from the collection center to the disposal center.

δ_r : The percentage of non-recyclable glass waste being transported from the collection center to the disposal center.

δ_v : The percentage of non-recyclable steel waste being transported from the collection center to the disposal center.

β_k : The percentage of unrecovered plastic waste being transported from the recycler to the disposal center.

β_r : The percentage of unrecovered glass waste being transported from the recycler to the disposal center.

β_v : The percentage of unrecovered steel waste being transported from the recycler to the disposal center.

- Capacities

F_l : Quantity of medical waste generated by hospital l.

$Mcap_n$: Capacity of collecting center n.

MPW_m : Capacity of plastic recycler m.

MGW_m : Capacity of glass recycler m.

MSW_m : Capacity of steel recycler m.

$Mcap_o$: Capacity of disposal center o.

UP_n : The upper limit for establishing collecting center n.

UP_{km} : The upper limit for establishing plastic recycler m.

UP_{rm} : The upper limit for establishing glass recycler m.

UP_{vm} : The upper limit for establishing steel recycler m.

- Decision variables

AM_{ln} : The quantity of waste transported from hospital l to collection center n.

AM_{nkm} : The quantity of plastic waste transported from collection center n to recycler m.

AM_{nrm} : The quantity of glass waste transported from collection center n to recycler m.

AM_{nvm} : The quantity of steel waste transported from collection center n to recycler m.

Y_n : 1 if the collecting center n is opened, 0 otherwise.

Y_{km} : 1 if the plastic recycler center m is opened, 0 otherwise.

Y_{rm} : 1 if the glass recycler center m is opened, 0 otherwise.

Y_{vm} : 1 if the steel recycler center m is opened, 0 otherwise.

C. Social Objective Functions

- Job Creation Opportunities

Employment is a key driver of social sustainability, significantly influencing the well-being and socio-economic status of individuals [32]. A study by the [33] projects a potential net job creation of up to 700,000 jobs in the EU. Specifically, employment in waste management is anticipated to witness a substantial increase, with a potential addition of 660,000 jobs. This increase is attributed to the labor-intensive nature of recycling, which is replacing less labor-intensive landfilling practices.

$$\boldsymbol{Max\ Job\ Creation} = Fixed\ job\ creation (FJC) + Variable\ Job\ Creation\ (VJC) \quad (1)$$

$$\boldsymbol{FJC} = \sum_{n=1}^{N} DJ_n \times Y_n \times \mu_n + \sum_{m=1}^{M}\sum_{k=1}^{K} DJ_{km} \times Y_{km} \times \mu_{km} + \sum_{r=1}^{R}\sum_{m=1}^{M} DJ_{rm} \times Y_{rm} \times \mu_{rm} + \sum_{v=1}^{V}\sum_{m=1}^{M} DJ_{vm} \times Y_{vm} \times \mu_{vm} \quad (1\text{-}1)$$

$$\boldsymbol{VJC} = \sum_{l=1}^{L}\sum_{n=1}^{N} IDJ_n \times \frac{AM_{ln}}{Mcap_n} \times \mu_n + \sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{m=1}^{M} IDJ_{km} \times \frac{AM_{nkm}}{MPW_{km}} \times \mu_{km} + \sum_{n=1}^{N}\sum_{r=1}^{R}\sum_{m=1}^{M} IDJ_{rm} \times \frac{AM_{nrm}}{MGW_m} \times \mu_{rm} + \sum_{n=1}^{N}\sum_{v=1}^{V}\sum_{m=1}^{M} IDJ_{vm} \times \frac{AM_{nvm}}{MSW_m} \times \mu_{vm} \quad (1\text{-}2)$$

The objective function (1) is designed to maximize both fixed and variable job creation opportunities within the network. Eq. (1-1) specifically represents the fixed job creation in the collecting and recycling centers. The inclusion of unemployment rates μ_n, μ_{km}, μ_{rm}, μ_{vm} in the objective function allows the model to adapt its assessment of job creation based on the prevailing employment conditions, making the optimization more realistic and reflective of the socio-economic context. When the unemployment rate is high, indicating a substantial pool of unemployed individuals in the considered region or sector, the model recognizes that the potential for job creation through the recycling process could have a more substantial positive impact on the local workforce. Conversely, in the case of a low unemployment rate, signifying a smaller proportion of unemployed individuals, the model exerts less influence, as the employment market is presumed to be more saturated. Equation (1-2) defines the variable job creation in the collecting and recycling centers. The utilization of the ratios, including $\frac{AM_{ln}}{Mcap_n}$, $\frac{AM_{nkm}}{MPW_m}$, $\frac{AM_{nrm}}{MGW_m}$, $\frac{AM_{nvm}}{MSW_m}$ serves as a measure of how much of the capacity of collecting center n and recycler center m is being utilized. A ratio close to 1 indicates that there is potential for additional job opportunities.

- Balanced Economic Development

Balanced economic development serves as a positive social indicator, emphasizing a fair and inclusive distribution of economic benefits. This approach aims to mitigate income inequality by creating job opportunities across diverse sectors and regions, ultimately elevating overall living standards. The ripple effect of this strategy extends to an enhanced quality of life, fostering social cohesion, and empowering communities. In essence, a commitment to balanced economic development reflects a dedication to creating a more equitable and thriving society.

$$Max\ ED = \sum_{n=1}^{N} V_n \times Y_n \times (1 - rd_n) + \sum_{m=1}^{M}\sum_{k=1}^{k} V_{km} \times Y_{km} \times (1 - rd_{km}) + \sum_{m=1}^{M}\sum_{r=1}^{R} V_{rm} \times Y_{rm} \times (1 - rd_{rm}) + \sum_{v=1}^{V}\sum_{m=1}^{M} V_{vm} \times Y_{vm} \times (1 - rd_{vm}) \quad (2)$$

The objective function (2) represents the economic development associated with each collection center and recycling center. The terms rd_n , rd_{km}, rd_{rm} , rd_{vm} in the objective function serve as adjusters, strategically considering the impact of regional development on the economic value associated with the proposed model. These adjusters play a crucial role in accounting for the varying degrees of regional development and tailor the objective function to reflect the nuanced economic landscape, ensuring a more accurate representation of the model's objectives in the context of different regions.

D. Constraints

- Supply Constraints

$$\sum_{l=1}^{L} AM_{ln} \le F_l \ \ \forall n \quad (3)$$

This constraint guarantees that the amount of waste collected from each hospital is limited to the quantity of waste generated by that specific hospital.

- Flow Balance Constraints

$$\sum_{l=1}^{N} AM_{nkm} = \sum_{l=1}^{N} AM_{ln}\ (1 - \delta_k)\ \ \forall\, \mathrm{l, m, k} \quad (4)$$

$$\sum_{l=1}^{N} AM_{nrm} = \sum_{l=1}^{N} AM_{ln}\ (1 - \delta_r)\ \ \forall\, \mathrm{l, m, r} \quad (5)$$

$$\sum_{l=1}^{N} AM_{nvm} = \sum_{l=1}^{N} AM_{ln}\ (1 - \delta_v)\ \ \forall\, \mathrm{l, m, v} \quad (6)$$

Eq. (4), (5) and (6) Ensure that the total waste received at collection centers is equivalent to the total waste forwarded to recycling centers, considering potential damage.

- Capacity Constraints

Maximum capacity can be allocated to collecting center n.

$$\sum_{n=1}^{N} AM_{ln} \le Mcap_n \times Y_n\ \forall \mathrm{l} \quad (7)$$

Maximum capacity can be allocated to recycling center r.

$$\sum_{m=1}^{M} AM_{nkm} \le MPW_m \times Y_{mk}\ \forall\, \mathrm{n, k} \quad (8)$$

$$\sum_{m=1}^{M} AM_{nrm} \le MGW_m \times Y_{mr}\ \forall\, \mathrm{n, r} \quad (9)$$

$$\sum_{m=1}^{M} AM_{nvm} \le MSW_m \times Y_{mv}\ \forall\, \mathrm{n, v} \quad (9)$$

Constraints (11), (12), (13), and (14) determine the upper limit on the number of collecting centers and recycling centers that can be opened.

$$\sum_{n=1}^{N} Y_n \le UP_n \quad (11)$$

$$\sum_{m=1}^{M} Y_{mk} \le UP_{mk}\ \ \forall \mathrm{k} \quad (12)$$

$$\sum_{m=1}^{M} Y_{mr} \le UP_{mr}\ \forall \mathrm{r} \quad (13)$$

$$\sum_{m=1}^{M} Y_{mv} \le UP_{mv}\ \forall \mathrm{v} \quad (14)$$

Finally, Constraint (15) and (16) enforce the binary and no negativity restrictions on corresponding decision variables.

$$Y_n, Y_{mk}, Y_{mr}, Y_{mv} \in \{0{,}1\} \quad (15)$$

$$AM_{ln}, AM_{nkm}, AM_{nrm}, AM_{nvm} \ge 0 \quad (16)$$

IV. SOLUTION APPROACH

A. Artificial bee Colony Algorithm

The optimization algorithms based on swarm intelligence have come to be considered as one of the best methods for handling difficult real-world problems. The Artificial bee colony (ABC) is one of such optimization algorithms based on swarm intelligence, The ABC algorithm, introduced by [34], is an optimization algorithm inspired by the foraging behavior of honeybees. This algorithm is specifically designed to systematically explore and exploit potential solutions in the context of optimization problems. The ABC algorithm comprises as shown in Fig. 2, three distinct categories of bees: employees, onlookers, and scouts. First, employee bees are dispatched to diverse food sources, each with a designated location. These employees assess the nectar quantity associated with their designated food sources. At the same time, onlooker bees stay within the hive, systematically collecting crucial information about food sources with superior nectar levels, as communicated by the employee bees. Subsequently, onlooker bees influence the directional shifts for employee bees to explore further, based on the observed nectar quantity of each food source. Employee bees encountering stagnation in nectar accumulation may transform into scout bees, responsible for the stochastic discovery of new food sources. This dynamic interplay between exploration and exploitation is a core aspect of the ABC algorithm, reflecting the collaborative and adaptive dynamics inherent in natural honeybee colonies.

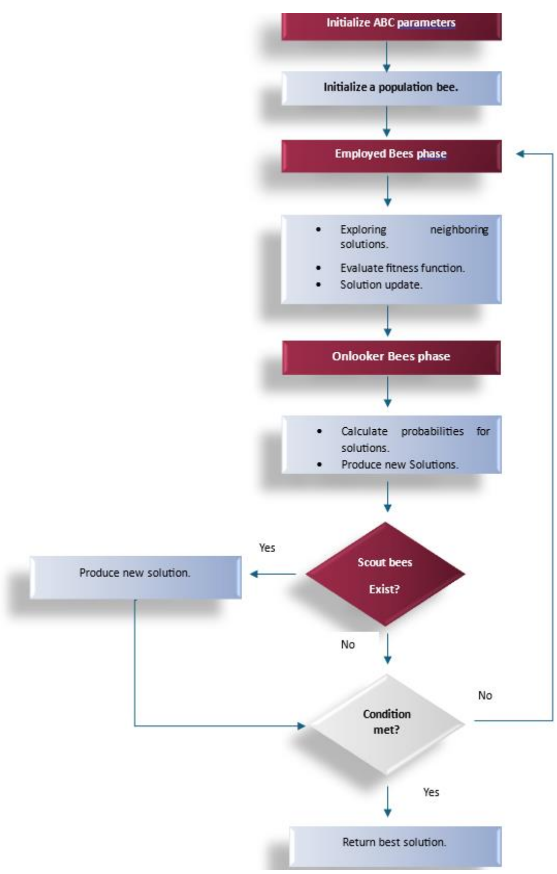

Fig. 2. Flowchart of artificial bee colony.

B. Genetic Artificial bee Colony Algorithmthe

In order to improve the exploration and exploitation capabilities of the ABC algorithm, a genetic algorithm is incorporated. This integration, specifically introduced into the employed phase of an Artificial Bee Colony (ABC), brings forth genetic operations like crossover and mutation. These genetic operations play a pivotal role in broadening the exploration of the solution space. The refined solutions produced by employed bees, through the application of genetic operations, contribute to a more thorough exploration, ultimately improving the overall performance of the algorithm. A comprehensive explanation of the hybridization process is presented below.

1) Initialization of prameters: In this initialization phase of the algorithm, critical parameters are defined to shape its behavior. The population size (PS) is determined, outlining the number of individuals constituting the population. Simultaneously, the number of food sources is established, each representing a potential solution within the optimization problem. The symmetry between employed and onlooker bees is emphasized, ensuring an equal distribution of roles in the algorithm. The maximum number of iterations is specified, delineating the extent of the algorithm's exploration and refinement cycles. A cycle limit is also set. Finally, the algorithm's initial population is initialized with bees, each carrying random solutions that signify quantities of waste transported between facilities. These defined parameters and the initial population collectively lay the foundation for subsequent algorithmic phases, guiding its systematic approach to solution exploration and optimization.

2) Employed bee phase: In the Artificial Bee Colony Algorithm, employed bees actively explore their surroundings in search of alternative food sources that offer higher nectar content than their current location.

- Exploring neighboring solutions: Employed bees explore neighboring solutions, conducting a systematic search for alternative options that reside in close proximity within the solution space.
- The fitness: To compute the fitness value for the current solution based on the objective function. The fitness is determined through the following Eq. (18):

$$fitness_i = \frac{1}{1+Gi} \tag{18}$$

Where $fitness_i$ is the fitness of the associated solution. Gj represents the objective function for the jth Solution.

- Solution Update: When the newly explored solution surpasses the previous one in terms of both job creation and economic development, the employed bee proceeds to update its solution.

3) Genetic operators phase: In this part the algorithm executes genetic operators, such as crossover and mutation, to introduce genetic variation and improve the solutions.

To choose a pair of parents from the solutions acquired through employed bees, it is essential to establish an encoding scheme for this problem. As shown in Fig. 3 and Fig. 4, this model employs a hybrid encoding, integrating both binary and floating encodings to represent the chromosome. For example, considering five hospitals, two collecting centers, three plastic recyclers, two glass recyclers, and two steel recyclers, each chromosome can be represented by (2+3+2+2+5*2+2*3+2*2+2*2+3*2+2*2+2*2) array. The initial (2+3+2+2) genes denote whether the two collecting centers are open (1) or closed (0). The same logic applies to plastic recyclers, glass recyclers, and steel recyclers. Following this, the next set of genes (5*2) represents the quantity of waste generated by the five hospitals and transported to the collecting centers. Subsequently, the sequences (2*3), (2*2), and (2*2) signify the amounts of waste transported from collecting centers to plastic recyclers, glass recyclers, and steel recyclers, respectively. Finally, the last set of genes (3*2), (2*2), and (2*2) represent the unrecovered waste transported from plastic recyclers, glass recyclers, and steel recyclers.

As illustrated in Fig. 3, the first row comprises two elements representing the collecting centers, followed by three elements for plastic recyclers, two for glass recyclers, and the last two elements for steel recyclers. Meanwhile, the second row defines an example of the binary encoding scheme.

In Fig. 4 an example of the floating encoding scheme is defined, the first table represents the Amount N_{ij} of waste generated by the hospital i and shipped to the collecting center j. The subsequent table defines the quantity M_{ijk} of plastic waste k transported from the collecting center i to plastic recycler j. The following table represent defines the quantity P_{ijk} of glass waste k transported from the collecting center i to glass recycler j. The last table represents the quantity R_{ij} of steel waste transported from the collecting center i to steel recycler j.

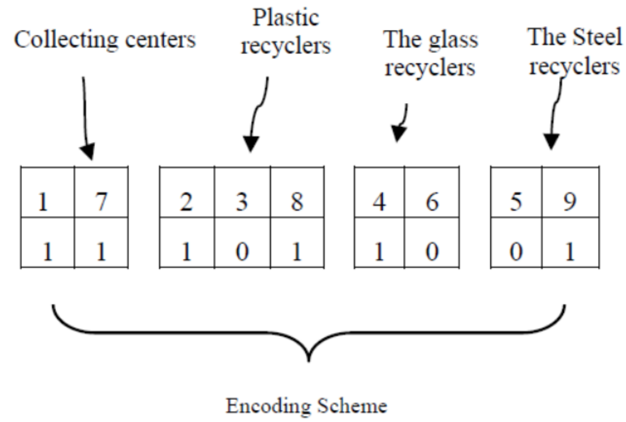

Fig. 3. Example of the binary representation.

Quantities of generated waste in hospitals shipped to collecting centers					
N_{11}	N_{ij}	N_{51}	N_{12}	…	N_{52}
6356	…	5438	7685	…	3574

Quantities of waste shipped from collecting centers to plastic recyclers					
M_{111}	M_{ij1}	M_{231}	M_{112}	M_{ij2}	M_{232}
3452	…	1342	5432	…	3572

Quantities of waste shipped from collecting centers to glass recyclers					
P_{111}	…	P_{221}	P_{112}	…	P_{222}
2314	…	1931	3285	…	4362

Quantities of waste shipped from collecting centers to steel recyclers			
R_{11}	R_{21}	R_{11}	R_{22}
1462	965	2563	4362

Fig. 4. Example of floating encoding scheme of solution.

- Select Parent food source

Before testing the performance of integrating the genetic algorithm into the ABC algorithm by applying genetic operators, we need to select two of the best parents obtained by the employed bees solutions using the Tournament selection. These parents contribute to the creation of offspring through crossover and mutation operations.

- The Crossover Operator

After selecting the two best solutions obtained from employed bees as parents, the crossover is applied. Crossover is a genetic operator that combines the genetic material of the two selected parents to generate two new offspring.There are various types types of mutation exist, such as bit-flip mutation, of cross over one-point crossover, multi-point crossover, and uniform crossover in this study we use one-point crossover. A one-point crossover point is randomly chosen along the length of the parent chromosomes, this procedure involves cutting a chromosome at a specific position and switching the ends between the two parents.

- The mutation Operator

After the crossover operation, we apply the mutation operator to the two new offspring obtained. The mutation operator is another genetic operator that involves introducing small changes to one or more genes in chromosomes. Differents random mutation, inversion mutation, displacement mutation, and swap mutation. In this paper, we apply the swap mutation, where two positions within the permutation are randomly chosen, and the elements at those positions are swapped.This operation helps to improve the exploration of new solotions.

- The new solution update

In this step, we substitute the worst solution acquired from the employed bees with the new offspring. The updated solutions with the information about the quality and location of their food sources are then communicated to the onlooker bees.

4) Onlooker bee phase

- The Probability

In this phase, onlookers utilize the information shared by the employed bees to determine whether the food source should be further explored in search of better solutions or if the food source should be sent to scout bees. The probability of selecting a specific food source for exploration is presented in Eq. (19), where the higher fitness has a higher probability to be chosen.

$$Pi = \left(\frac{fitness_i}{\sum fitness_i}\right) \quad (19)$$

The onlooker bees use the probability Pi to guide the employed bees toward the higher quality areas of solution space.

- Produce new solutions

Following the exploration of solution spaces, we assess the newfound fitness in comparison to the previous fitness. If the new solution provides better fitness, we substitute the previous solution; otherwise, we maintain the previous solution. This iterative process continues until the maximum number of iterations is achieved.

5) Scout bee phase: The bees that fail to demonstrate improvement in their associated food source transition into scout bees. This is because employed bees repeatedly exploring the same food source are no longer discovering useful information.

V. Computational Results

A. GABC Algorithm Parameters

To assess the effectiveness of the proposed GABC algorithm, we applied the Taguchi method [35]. This method is used to determine the optimal combination of GABC algorithm parameters by identifying the factors that influence the performance and effectiveness of GABC algorithm. In this paper, we considered three factors Table I: population size, iteration number, and limit cycle which represents the maximum number of times an employed bee can revisit the same food sources without improvement. Each factor was explored at three levels: 1 for low, 2 for medium, and 3 for high. The next step is to apply the Taguchi orthogonal array (OA) to design a set of experiments covering all combinations of the selected factors. In the proposed model, Table II shows that each parameter is tested across three levels, with three experiments for each level, resulting in a total of 9 tests.

TABLE I. Presentation of Different Factors and Levels

Levels	Population Size	Iterations	Limit cycles
1	60	100	15
2	120	200	20
3	180	300	25

The experiments presented in Table II, using the orthogonal array (OA), generate a series of combinations that aid in identifying the best combination providing the optimal performance for the proposed model among all the obtained combinations.

TABLE II. The Taguchi Orthogonal Array

Experiment	Levels		
	Population Size	**Iterations**	**Limit cycles**
1	1	2	2
2	1	3	3
3	1	1	1
4	2	1	2
5	2	2	1
6	2	3	3
7	3	3	3
8	3	2	2
9	3	1	1

After using orthogonal arrays and conducting experiments at different factor levels, The Signal-to-Noise (S/N) is calculated for each experimental using Eq. (20).

$$S/_N = 10\ \log\left(\frac{(mean)^2}{(Variance)^2}\right) \quad (20)$$

Where the meanor signal represents the average performance of the objective function, Variance measures the extent to which each individual number in a set deviate from the mean, or average, of those numbers. In the following section, we will present the best combination obtained by utilizing the orthogonal array (OA) and Signal-to-Noise (S/N) ratio.

B. Numerical Result

The provided problem was implemented in python and executed in an Intel (R) Core (TM) i5-6300U Processor 2.67GHz with 8 GB of RAM.

To proceed with the numerical testing and confirm the efficacy and validity of the proposed model, we are addressing both small and large problems. To account for the uncertainties in the proposed model, we take into consideration different scenarios for each size. As mentioned earlier, studies conducted in the field of medical waste are limited, and most countries prefer not to disclose the actual situation of generated medical waste. This makes obtaining data somewhat challenging. As mentioned earlier, studies conducted in the field of medical waste are limited, and most countries prefer not to disclose the actual situation of generated medical waste. This makes obtaining data somewhat challenging. To address this challenge, we have reviewed various existing studies in the literature and non-government reports that address the problem of medical waste to collect data. Specifically, we are concentrating on these two studies [36], [37] to gain an idea of the average amount of waste generated by hospitals. In this paper, as illustrated in Table III, we address three types, and for each type, we focus on a specific product.

1) Small problem: For a small problem size, we examined a network comprising 10 nodes. These nodes include four hospitals, two collecting centers (with a requirement for one collecting center to be opened), two plastic, one glass recycler, and one steel recycler, as shown in Table III. To tackle the uncertainties of the waste generated by the hospitals, we considered six scenarios, as illustrated in Table *IV*. The best combination for the different levels of the Taguchi method presented in the last section for the small size plus the genetic parameters are presented in Table V.

2) Large problem: In this part of the problem, we considered a network with 17 nodes, including 8 hospitals, 3 collecting centers (with one required to be opened), 3 plastic recyclers (with one plastic recycler required to be opened), 2 glass recyclers (one of which is required to be opened), and a steel recycler, as shown in Table VII. We considered six scenarios for the quantities of waste generated by hospitals in Table VIII. The Table IX presents the optimal combination for the proposed model using the Taguchi method.

TABLE III. TYPES OF MEDICAL WASTES

Waste types	Characteristic	
Plastic	• Polyethylene (PET) • Polypropylene (PP)	- Some medical containers, - Syringes, medical vials, and other medical containers.
Glass	• White glass • Brown glass	- -
Steel	• Stainless Steel	-

TABLE IV. THE VALUE OF THE PROPOSED MODEL

Set	Value
Hospitals	4
Collection centers	2
Plastic recyclers	2
Glass recyclers	1
Steel recyclers	1
$\boldsymbol{\delta_k}$	5%
$\boldsymbol{\delta_r}$	7,5%
$\boldsymbol{\delta_v}$	9%
$\boldsymbol{\beta_k}$	15%
$\boldsymbol{\beta_r}$	20%
$\boldsymbol{\beta_v}$	24%
$\mathbf{Mcap_n}$	Uniform (0,32000)
$\mathbf{MPW_m}$	Uniform (0,20000)
$\mathbf{MGW_m}$	Uniform (0,15000)
$\mathbf{MSW_m}$	Uniform (0,15000)

TABLE V. THE WASTE GENERATED IN EACH HOSPITAL

	H1			**H2**			**H3**			**H4**		
	Plastic	**Glass**	**Steel**	**Plastic**	**Glass**	**Steel**	**Plastic**	**Glass**	**Steel**	**Plastic**	**Glass**	**Steel**
1	1754	382	133	2043	548	184	2554	845	285	3264	1253	876
2	1968	424	165	2300	722	210	2765	975	276	3678	1578	1045
3	2265	653	189	2310	863	263	3200	1056	332	4003	1893	1357
4	2536	750	223	2740	950	350	3505	1130	376	4284	2193	1543
5	2705	811	345	3098	1124	431	3920	1321	409	4763	2367	1713
6	3087	854	409	3176	1326	504	4205	1530	532	5123	2431	1923

TABLE VI. THE OPTIMAL TAGUCHI METHOD COMBINATION FOR SMALL PROBLEM

	GABC			**GA**	
	Population size	Number of iterations	Limit number of cycles	Crossover rate	Mutation rate
Small problem	120	100	15	0.9	0.1

TABLE VII. THE VALUE OF THE PROPOSED MODEL

Set	Value
Hospitals H	8
Collection centers C	3
Plastic Recyclers	3
Glass Recyclers	2
Steel Recyclers	1
$\boldsymbol{\delta_k}$	5%
$\boldsymbol{\delta_r}$	7,5%
$\boldsymbol{\delta_v}$	9%
$\boldsymbol{\beta_k}$	15%
$\boldsymbol{\beta_r}$	20%
$\boldsymbol{\beta_v}$	24%
$\boldsymbol{Mcap_n}$	Uniform (0,32000)
$\boldsymbol{MPW_m}$	Uniform (0,20000)
$\boldsymbol{MGW_m}$	Uniform (0,15000)
$\boldsymbol{MSW_m}$	Uniform (0,15000)

TABLE VIII. THE WASTE GENERATED IN EACH HOSPITAL

	H1			**H2**			**H3**			**H4**			**H5**			**H6**			**H7**			**H8**		
	Plastic	**Glass**	**Steel**	**Plastic**	**Glass**	**Steel**	**Plastic**	**Glass**	**Steel**	**Plastic**	**Glass**	**Steel**	**Plastic**	**Glass**	**Steel**	**Plastic**	**Glass**	**Steel**	**Plastic**	**Glass**	**Steel**	**Plastic**	**Glass**	**Steel**
1	1754	382	133	2043	548	184	2554	845	285	3264	1253	876	1251	353	124	**8634**	2557	809	2224	733	458	5604	1339	576
2	1968	424	165	2300	722	210	2765	975	376	3678	1578	1045	2967	401	213	**9687**	2971	1480	2518	1270	598	6078	1874	643
3	2265	653	189	2710	863	263	3200	1056	400	4003	1893	1357	3088	687	357	**10964**	3893	1661	5623	1690	787	7003	2465	787
4	2536	750	223	2940	950	350	3505	1130	576	4284	2139	1543	3591	825	539	**14583**	4191	1855	6734	1998	961	8284	3475	833
5	2705	811	345	3298	1124	431	4920	1321	680	5763	2767	1713	3980	1054	761	**17654**	6367	2013	7698	3246	1123	9763	4361	913
6	3087	950	409	3376	1326	504	5605	2530	960	6123	3071	1923	4126	1329	933	**19872**	7031	2319	8763	3434	1456	10123	4783	1076

TABLE IX. THE OPTIMAL TAGUCHI METHOD COMBINATION FOR LARGE PROBLEM

	GABC			**GA**	
	Population size	Number of iterations	Limit number of cycles	Crossover rate	Mutation rate
Large problem	120	200	20	0.9	0.1

C. Results

In this section, we compare the results obtained by the proposed GABC algorithm and the Artificial Bee Colony algorithm using optimal parameters derived through the application of the Taguchi method. Table VI shows optimal Taguchi method. The primary objective is to maximize positive social indicators in the proposed model, emphasizing the creation of job opportunities while maintaining a balance in economic development. We employed a weighted sum formulation approach, assigning equal weights (0.5, 0.5) to two objective functions, signifying an equal contribution of both objectives to the overall objective function.

For the unemployment rate and region development rate, we explore three different values for both small and large problems, as outlined in Table X and Table XI. Additionally, the assumption is made that all facilities are located within the same region. The economic value is centered on two aspects: cost savings achieved through the recycling of medical waste and revenue generated by purchasing recovered waste for use in creating new products.

1) Results for small problem: To calculate our second objective function, as shown in Table X, it is imperative to quantify the regional development rate. The term 'regional development' includes economic it is imperative to quantify the regional development rate. The term 'regional development' includes economic, environmental, it is imperative to quantify the regional development rate. The term 'regional development' includes economic, environmental, and social progress within a specific region.

The primary goal of regional development is to enhance the overall well-being of the population in that region by addressing economic disparities, improving infrastructure, and promoting address multidimensional poverty rates, where we will examine three different rates of multidimensional poverty.

TABLE X. THE RESULTS FOR SMALL PROBLEM

Unemployment rate	Multidimensional poverty rate	Scenario	GABC			ABC		
			Job creation opportunities	Economic development ($)	CPU Time	Job creation opportunities	Economic development ($)	CPU Time
5.4%	3.1%	1	122.53	8532.84	24.56	111.68	7890.85	2.32
		2	134.31	9797.51	37.45	127.25	9323.96	4.16
		3	148,75	11454.27	49.03	148.43	11384.48	5.59
		4	169.37	14861.46	65.76	160.4	13769.98	8.48
		5	195.75	16903.55	88.92	192.5	16879.39	9.52
		6	212.83	19601.61	95.30	204.75	19273.93	11.27
10.3%	11.9%	1	207.32	7187.83	25.67	201,89	7098.67	3.52
		2	226.91	8608.76	36.73	214.25	8477.20	4.33
		3	257.18	9954.29	51.98	250.9	9863.08	5.12
		4	282.34	12265.83	66.23	274.3	11007.61	8.61
		5	338.28	14667.73	89.45	334.41	14873.90	10.39
		6	383.78	17165.15	97.43	375.62	17983.01	12.52
16.1%	24.3%	1	301.04	6057.44	25.55	292.86	6164.47	3.83
		2	336.25	7220.63	37.92	329.34	7284.04	5.08
		3	384.05	8765.48	54.76	375.1	8619.85	7.81
		4	419.39	10876.75	68.15	408.98	10237.03	9.69
		5	517.43	12870.16	90.95	500.36	12634.83	12.72
		6	584.00	14936.95	96.45	572.3	14763.11	13.65

TABLE XI. THE RESULTS FOR LARGE PROBLEM

Unemployment rate	Multidimensional poverty rate	Scenarios	GABC			ABC		
			Job creation opportunities	Economic development ($)	CPU Time	Job creation opportunities ($)	Economic development	CPU Time
5.4%	3.1%	1	435.96	18457.21	78.71	421.65	18340.74	3.42
		2	541.12	25551.47	96.32	503.91	25490.52	5.03
		3	625.87	29904.01	115.76	603.09	29865.07	6.34
		4	712.53	32435.81	131.04	699.1	32327.38	8.69
		5	784.01	36925.71	135.76	765.01	36897.89	10.98
		6	931,98	40112.49	158.22	923.81	40007.16	12.08
10.3%	11.9%	1	759.40	16982.07	78.88	735.79	16675.12	4.93
		2	931.43	21238.64	96.70	908.37	21084.77	5.17
		3	1100.24	24954.28	117.90	1096.06	24642,24	6.87
		4	1299.83	28003.91	136.77	1278.03	27890.73	9.02
		5	1438.19	31132.54	137.16	1405.75	30393.36	11.43
		6	1727.26	34532.17	167.49	1711.39	34198.10	12.91
16.1%	24.3%	1	1151.28	14548.62	79.78	1106.31	14328.15	5.34
		2	1412.34	19008.06	95.92	1380.4	18671.86	6.64
		3	1693.59	23067.30	117.84	1670.63	22893.58	7.09
		4	2007.11	25876.49	136.01	1985.72	25816.92	9.63
		5	2196.61	27958.38	137.53	2163.91	27893.38	11.92
		6	2658.02	31976.23	168.81	2631.69	31896.81	13.28

The results from Table X and Table XI indicate that the solutions obtained by the proposed GABC algorithm are better than the solutions obtained by the original ABC algorithm for the two objective functions. Additionally, the time required to execute the GABC code is longer than that of the ABC, attributed to the hybrid nature of the GABC algorithm, which combines two algorithms. The increased computational time is expected due to this hybridization.

Regarding job creation opportunities, is illustrated in Fig. 5, the value increases as the unemployment rate rises.

In Fig. 6, depicting economic development, we observe the opposite trend: the economic value decreases as the multidimensional poverty rate increases.

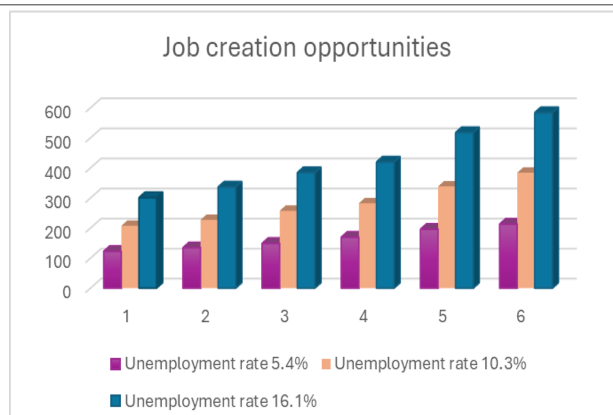

Fig. 5. Small problem comparison for different multidimensional poverty rates.

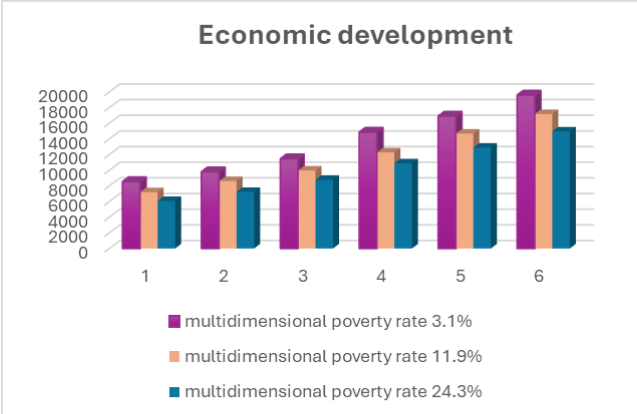

Fig. 6. Small problem comparison for different unemployment rates.

1) Results for large problem: Same as the small problem, for the large problem, the proposed GABC algorithm exhibits better results than those obtained by the ABC algorithm. In the job creation opportunities function for the large problem, there is an increase in regions with rising unemployment rates Fig. 7. This highlights the need for establishing more facilities in regions with high unemployment rates to address the issue. For the balanced economic development function Fig. 8, we observe that the region with higher multidimensional poverty experiences a decrease in economic development.

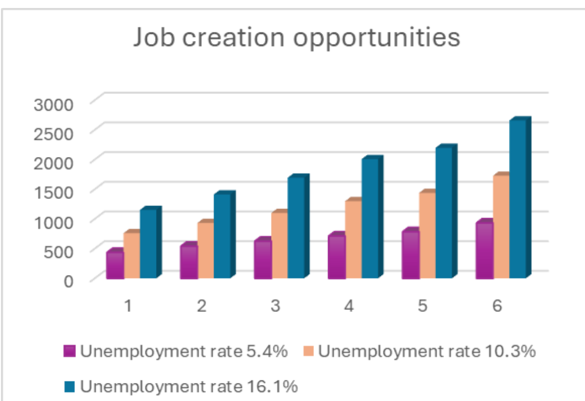

Fig. 7. Large problem comparison for different unemployment rates.

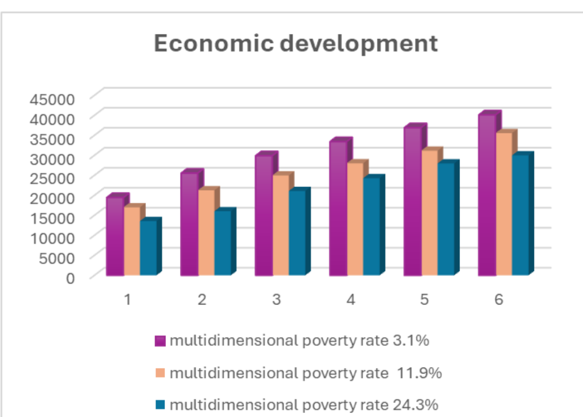

Fig. 8. Large problem comparison for different multidimensional poverty rates.

D. Discussion

In this paper, our objective is to maximize positive social indicators by focusing on job creation and balancing economic value. The results indicate that through the recycling of medical waste, we can generate more job opportunities and promote balanced economic development, thereby reducing social disparities and enhancing overall well-being.

Our research into the literature indicates a scarcity of studies focusing on the social impact of recycling end-of-life products. Specifically, few studies delve into issues such as job creation indicator or the number of days lost due to occupational accidents resulting from the construction of waste processing centers [25], [30], [38]. In light of this gap, our study aims to address the issue of multidimensional poverty, considering it as one of the positive indicators being investigated. Our examination of the existing literature highlights that this study marks the inception of discourse on this topic. The numerical results demonstrate that adopting sustainable practices to preserve natural resources and reuse them, using recycling principles, helps to create more job opportunities. This means decreasing the unemployment rate and multidimensional poverty, ultimately improving the quality of life for people.

VI. Conclusion

In this paper, we illuminate the often overlooked third dimension of sustainability in research, highlighting the significance of maximizing positive social indicators. Our hybrid approach, employing the Artificial Bee Colony (ABC) algorithm and Genetic Algorithm (GA) to tackle two objective functions: enhancing job creation opportunities and promoting balanced economic development. The paper focuses on the reverse supply chain for recycling medical waste, encompassing various stakeholders such as hospitals, collection centers, plastic recyclers, glass recyclers, and steel recyclers. To assess the performance and effectiveness of the proposed GABC algorithm, we conducted a comparative analysis with the ABC algorithm. We subjected the proposed approach to testing in diverse scenarios to simulate real-life situations.

The comparison between the proposed GABC and the original ABC indicates that the suggested approach consistently outperforms in various scenarios studied, providing superior solutions for both job creation opportunities and economic development. This success can be attributed to the nature of the proposed approach, which integrates two algorithms: ABC and GA.

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