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RESEARCH ARTICLE

An Innovative Algorithm-Driven Optimization Framework for Landfill Mining: Aiming Sustainable Profitability Expeditiously

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ABSTRACT Landfill mining (LFM) offers a potential solution to the environmental issues associated with landfilling. The current work aims to develop an efficient optimization framework for LFM that is sustainable, profit-yielding, and time minimizing at the same instance. The proposed framework involves a multi-objective multi-level solid transportation model (MOMLSTM). This model can be adapted by the organization across various geographies as it incorporates uncertainty of all the parameters of time, cost, and emission through pentagonal fuzzy numbers (PFN). The other crucial contribution of this work is the development of a genetic algorithm for offspring refinement (GAOR) that contributes in optimizing multi-objective optimization (MOO) problems. The GAOR's performance has been verified using the Congress on evolutionary computation (CEC) 2020 multi-objective benchmark test functions. GAOR is assessed against six robust MOO algorithms, including the multi-objective equilibrium optimizer slime mould algorithm (MOEOSMA), enhanced multi-objective particle swarm optimization (EMOPSO), multi-objective gorilla troops optimizer (MOGTO), adaptive crossover strategy enhanced NSGA-II (ASDMSGA-II), multi-objective slime mould algorithm (MOSMA), and multi-objective equilibrium optimizer algorithm (MEOA). GAOR delivered outstanding results across three crucial performance indicators. To rank these algorithms, a Friedman test was conducted, and GAOR achieved the highest ranking among the tested MOO algorithms. A case study is considered for real-life application of the model and solution technique GAOR. The outcomes of MOMLSTM from GAOR are compared to the epsilon-constraint method. The comparison revealed noteworthy improvements: a 0.14% increase in profits, a 1.29% reduction in carbon emissions, and a 3.81% decrease in the time required.

INDEX TERMS Epsilon-constraint method, genetic algorithm, multi-objective solid transportation problem, pentagonal fuzzy number, sustainable landfill mining.

I. INTRODUCTION

Landfills are among the most prevalent techniques for dumping solid waste because of their unique benefits that are hardly ever encountered elsewhere. These benefits embrace the simplicity with which landfills can be installed and the modest expenses accompanying both their establishment and running. Numerous landfills have been built worldwide, where garbage is stockpiled. Some of the biggest landfills of the world include Apex Regional in Las Vegas (Nevada), Laogang in Shanghai (China), Bordo Poniente, Mexico City (Mexico); they cover an area of around 22,200 acres, 1000+ acres, and 927 acres respectively [1].

Two main causes can be identified for the engrossment in conventional landfill facilities. First and foremost, important components involve plastics, metals, and rare substances like combustibles. However, these disposal facilities additionally trigger environmental problems since they discharge greenhouse gases (GHGs), which comprise methane (CH4) and carbon dioxide (CO2), experience leachate intrusion

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into the soil, and take up territory that may obstruct city extension. Mostly two kinds of waste are found in any landfill that is in operation municipal solid waste (MSW) and legacy waste (LW). There is a peculiar interlinkage among the living (biotic) and non-living (abiotic) materials at a landfill, which can be thought of as a self-contained ecosystem. This interlinkage distinguishes between new municipal garbage and legacy trash that has experienced transformations throughout time. Significant monetary losses are brought on by landfills. The cost of negative ecological impacts related to the Bhandwari dumpsite located in Gurugram in India, including contamination of the environment, water, soil, carbon emissions, and visually appealing complications, were estimated to be around Rs 148.46 crore [2]. A separate investigation demonstrated that three different landfills in Delhi at Bhalswa, Ghazipur, and Okhla have, throughout the years, resulted in roughly Rs 450 crore environmental harm [3]. Thus, clearing these landfills sustainability is the need of the hour. The most recent technique being used for clearing these landfills is LFM. Recovering resources that were formerly abandoned or thrown in garbage dumps, especially in the context of open landfills, is a practice referred to as LFM. In order to retrieve valuable resources from landfills, such as plastics, metals, glass, ignited materials, and other materials, it is deployed. The current trash is separated throughout this method, and the organic fraction is then transformed into compost that generates a gas called methane or bio-diesel. Following segregation, the non-reusable plastic is converted into fuels called refused-derived fuels (RFD) that can be utilized as a substitute for fossil fuels by various sectors. Additionally, the compost fraction of the trash is sieved out and marketed for use as fertilizer and soil enrichment in gardening or other applications [4]. However, LFM is still a developing field.

Many researchers have worked in this field. Some recent studies around this topic involve the research on identifying the primary reasons for improved LFM strategies, LFM functioning in the United States, Europe, India, and China [5], step-wise functioning of LFM in detail incorporating excavation-shredding-screening-refurbishing, importance of landfill site-specific feasibility study and advanced separation techniques [6], employment of customized geological piercing and extraction technologies for LFM [7], despite producing highly precious elements, mining waste rehabilitation has severe environmental effects [8], impact of LFM towards global warming [9] and job options arising due to LFM [10]. The entire steps of landfill mining, along with some bi-products, are shown in Figure 1. Few of the researchers have addressed crucial considerations like the economic viability of landfill mining. Some literature around this involves methodology for evaluating the investment costs and operating expenses of waste mining activities as well as the possible financial advantages, study on the use of an organized method that combines cost-benefit evaluation and multi-criteria analysis to identify landfill mining initiatives exhibiting the greatest commercial potential [10], simulation tool evaluating cost of mining steps like excavation-segregation-feasibility-reclamation [11], measuring commercial viability of landfill mining through land repossession and restoring energy [12], provision of new job offers due to LFM [10], environmental assessment followed by financial evaluation of enhanced LFM in Tehran was studied [10], review of the financial sustainability of LFM [13]. LFM encounters multiple uncertainties during its entire course; some of the literature that discusses uncertainty in LFM is the uncertainty of cost and benefits of LFM [14], uncertainty awakening due to the usage of modelling techniques and various social perspectives [15], the uncertainty of market [10], technology [16], and society [17], uncertainty across the exploration phase of LFM [18].

After traversing across the literature of LFM, it is observed that there is a huge need for landfill redemption plans that are highly sustainable and cost-effective and less time-consuming. There is an explicit and acute requirement of fraternizing industry and government with the intention of a sustainable model for LFM that targets maximizing profit which is in turn directly analogous to the cost of LFM, and price of value-added products received post-LFM from waste. The plan should incorporate the time consumption during the entire course of LFM due to the adverse impact of waste lying in landfills on air, water, and land within the vicinity of the landfills. Another important component that should be accompanied is the reduction of carbon emissions in the entire process, and the plan should be sustainable in the long run. Thus, in this research work a landfill mining framework is proposed that uses MOMLSTM and aims to provide a sustainable profit maximizing model for landfill mining. The model was developed using the base of the solid transportation problem proposed by Haley [19].

In the MOMLSTM introduced in this context, the three objectives engage in competition with each other, leading to the absence of singular perfect or global optimum solution. Instead, the solution method yields a collection of pareto optimal alternatives within the same search region. Metaheuristic algorithms (MAs) are the foundation of the optimization operation. To solve a variety of optimization problems, MAs work with a set of randomly chosen solutions and refine them using predetermined methods [20]. Lately, there has been a proliferation of MOO approaches in the literature. Numerous evolutionary methods that have been presented in the literature to solve multimodal and multi-objective functions have difficulty generating numerous related Pareto sets (PS) and a well-distributed Pareto front (PF). Achieving convergence and diversity in the decision and objective spaces naturally trade off with one another. It is common for one feature to suffer when another is improved. Therefore, our study is motivated by the complicated task of maintaining both convergence and diversification at the identical time in the decision and objective spaces. To mention some of these recently proposed algorithms that either lack in convergence or diversity; consider the ring topology based multi-objective PSO (RING_PSO_SCD) [21]. The algorithm struggles to achieve satisfactory performance in the objective space. While it does exhibit strong diversity in the decision space, the coverage of Pareto-optimal solutions is compromised, as their results have demonstrated. Another multimodal multi-objective algorithm based on differential evolution (MMODE_ICD) attained enhanced diversity in the objective space, yet sustaining diversity and convergence simultaneously in the decision space remains a persistent challenge for the algorithm [22]. The multi-objective slime mould algorithm (MOSMA) [23] demonstrates notable drawbacks, such as poor distinguishing within slime mould algorithm (SMA), a less-than-ideal combination of non-dominated arranging and fitness dimensions that lowers convergence precision on complex problems, a crowding distance mechanism that fails to adequately maintain solution variance in the archives, resulting in a Pareto front that is not sufficiently distributed, and the inability to improve SMA's global search capability, which leaves MOSMA incompletely explored in the decision space. Multi-objective gorilla troops optimizer (MOGTO) is and updated version of GTO [24], it attains the best results and exhibits effective convergence toward real Pareto-optimal groups. Nevertheless, there are certain constraints associated with it i.e. When optimizing multi-objective (MO) problems with only three or four objectives, MOGTO is appropriate. Like other Pareto dominance-based techniques, MOGTO becomes less efficient as the number of targets rises. This is the case since for problems with over four objectives, a large fraction of alternatives falls into the non-dominated category, which causes the archive to fill up quickly. The MOGTO method is therefore best suited for solving problems with none more than three to four objectives.

A novel MA called GAOR has been presented to overcome the issues with the current MAs intended for MOO. The genetic algorithm (GA) and the local search (LS) algorithm are combined to create the hybrid algorithm known as GAOR. To strike the ideal equilibrium among attempts at intensification and diversification, the LS component is incorporated. Following mutation, LS is performed by using a random function to generate indices and switching between intermediate values. This LS integration greatly improves the global search performance of the MA. In GAOR, numerous swaps are iteratively tested using a systematic approach. The procedure comes to an end when the best improvement identified through each swap is kept, and if no improvement is found, the original solution is left unchanged. Additionally, GAOR has an adaptable search area that allows it to strike a balance between local and global search tactics while adapting to the solution space's topology. To assess the effectiveness and efficiency of GAOR, the research utilized the CEC 2020 test suite for evolutionary computation. Upon evaluating various performance indicators, it was evident that GAOR surpassed other established metaheuristic algorithms designed for MOO.

The proposed model encompassed most uncertainties stumbled during LFM, including uncertainty of waste composition (impacting pre-feasibility cost, bio-inoculation cost, waste processing cost, sorting cost), uncertainty in transportation due to weather and natural calamity (impacting cost of transportation, carbon emission, and time), uncertainty in market (impacting demand, supply, and price of value-added products). In the past many researchers have used fuzzy to capture uncertainties in transportation environments using fuzzy like [25] and [26]. All these uncertainties are captured in the proposed MOMLSTM using a PFN. PFN has been used in the past for solving solid transportation problem (STP) by various authors [27] and [28]. STP is used in past to develop profit maximizing model [29]. As the proposed model is MOMLSTM thus, a non-deterministic compromise solution technique is proposed in this paper by the name of GAOR. Genetic algorithm is used by many researchers for solving multi-objective, solid transportation problems to mention some [30] and [31]. There are many authors who tried developing multiple models to handle different objectives of landfill mining cost assessment, carbon emission, and time. Some of these works that capture the objectives of these model along with the environment they captured, be it uncertain or not, and the solution techniques availed along with sensitivity analysis are summarized in Table 1. Some of these works that capture the objectives of these model along with the environment they captured, be it uncertain or not, and the solution techniques availed along with sensitivity analysis are summarized in Table 1.

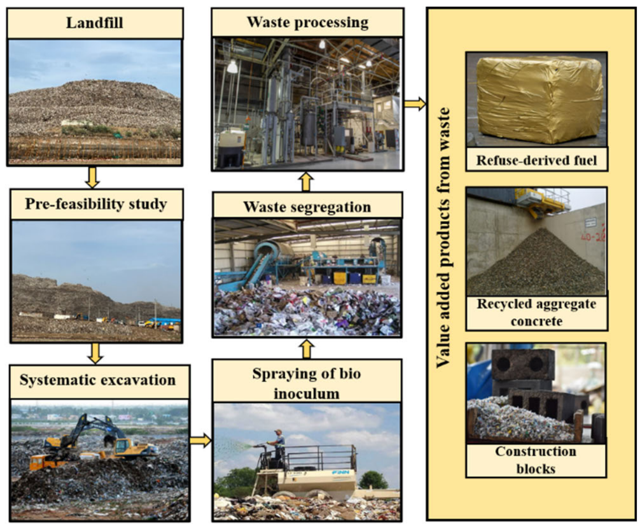


FIGURE 1. Landfill mining design with relevant steps and bi- products.

While there exists a substantial body of literature concerning landfill mining, there remains a limited amount of research that specifically addresses and resolves the fiscal and environmental challenges associated with landfill mining through the application of efficient mathematical models solved by MAs. The main motivation of this research paper involves:

- The strong incentives for maximizing profits within the landfill mining sector that provide a compelling rationale for the creation of an extensive mathematical model. The need of such model is highlighted in past by various researchers [15], [32].

- Lack of models that has the potential to offer invaluable insights into the optimization of resource recovery, reduction of operational expenses, and the pursuit of environmental sustainability objectives. Scarcity of endeavor yielding benefits that extend to both the industry and the ecological landscape.
- The research paper that handled uncertainty in landfill mining in past mentioned that there are certain aspects of landfill mining under which uncertainty is not tackled yet [33], [34]. This includes temporal variability in waste lying in landfills due varying time period deposition, spatial variability of waste that contributes to uncertainty in time and cost of waste management. Discrepancies in decomposition process often create uncertainty in the overall time, cost, and carbon emission of landfill mining.
- In the context of the MOO algorithm proposed in this paper, the primary driving force stems from the fact that despite numerous research efforts aimed at mitigating the inherent trade-offs between coverage and convergence in both the decision space and objective space of MOO algorithms, a significant research gap remains concerning the diversity and distribution of the PS. Furthermore, it is worth noting that only a limited number of MOO algorithms are capable of effectively handling more than three to four objectives, which is inadequate for addressing the complexity of objectives encountered in many real-world case studies. Hence, there is a pressing need for an advanced algorithm capable of accommodating a higher number of objectives.

The major contribution of this research paper can be listed as follows:

- The research article develops a mathematical MOMLSTM for landfill mining that aims to maximize overall profit and minimize carbon emissions and time. This model can be used by any government or non-government organization that takes tender of clearing landfills as they attribute to being a major hazard to the environment.
- Uncertainty in LFM associated with cost, time, carbon emission, demand, and carbon cap arising due to composition of waste, range of contamination, heterogeneous waste type, instability in landfill, weather, and regulatory compliance is captured using PFN, latest defuzzification technique is employed for accurate results.
- As the MOMLSTM has multiple objectives, thus a non-deterministic approach named GAOR is proposed in the research article for solving it and other similar models. Verification of the proposed technique with previous work is also performed.
- The organization engaged in landfill mining will benefit from the thorough sensitivity analysis that is completed at the conclusion. It helps establishments to take decisions about the economic and environmental stability of landfill mining. Each portion of this research article plays a vital role in delivering the above-mentioned contribution. In order to elucidate, Section II deep dives into the background information for developing optimization framework for landfill mining using mathematical model and impart information on how different objectives in MOMLSTM are built. Section III includes details of model formulation. It imparts details of all the indices, decision variables, parameters, objectives, and constraints developed. Under this section, all three objectives, along with the corresponding constraints, are presented for a complete knowledge of the model, and each of these details is discussed. The crucial principles for understanding uncertainty captured by PFN are covered in section IV. Following the definition of PFN, the process of defuzzification is illustrated with the proper graphic representation in this section. The proposed algorithm for solving MOMLSTM i.e., GAOR is thoroughly explained in Section V, accompanied by the methodology and relevant parameter selection technique for the algorithm. A numerical experiment utilizing a case study is presented in Section VI, along with the solution to the MOMLSTM problem using GAOR. Two distinct types of validation are then presented, and the section concludes with managerial reflections. The conclusion and anticipated scope are summarized in Section VII.

II. BACKGROUND FOR DEVELOPING OPTIMIZATION FRAMEWORK FOR LANDFILL MINING USING MATHEMATICAL MODEL

The technique of LFM assists in reclaiming resources and lessening the environmental risks roped with dumping grounds and landfills throughout the world. However, a major obstacle towards systematized LFM is efficiently handling the garbage created amid the rehabilitation of exposed and ancient dumpsites. LFM is a useful strategy for reclaiming land and reducing the ecological threats associated with waste disposal facilities across the world. It is crucial to determine the possible impact of pollutants, including leftovers in the extracted component. Fresh items generated post appropriate assessment and treatment of landfill waste can be sent back to the market, which is a profitable procedure. While systematic mining activities are performed on old garbage sites, a viable business model is produced.

Bio capping along with biomining are two widely used methods for restoring landfills. The bio-capping technique entails lining the landfill with high-density polyethene, clay liner, and cover from vegetation. The underlying idea is to prevent precipitation from seeping into the trash. The systems for gathering and processing waste water, also called leachate and landfill waste gas, have been implemented. Yet it simply is not physically possible to collect all these gases coming from landfill and leachate from a non-scientific dump.

Although capping seems like an instantaneous means to remediate a dumpsite, it fails to revitalize the soil or guarantee that residual garbage is treated scientifically. Thus, it leaves behind persistent risks to human health and the environment.

TABLE 1. Summary of literature related to mathematical models for landfill mining.

Research article	Geographical location	Objective function			Mathematical programming type	Consideration of Uncertainty	Solution technique		Sensitivity analysis
		Economic	Environmental	Time			Deterministic	Non-deterministic	
[33]	Mexico	✓	×	×	MILP	×	✓	×	✓
[34]	Abu Dhabi	✓	✓	×	MINLP	×	✓	×	×
[35]	Hong Kong	✓	×	×	LP & MILP	✓	✓	×	✓
[36]	Iran	✓	✓	×	MILP	×	✓	×	×
[37]	Iran	✓	✓	×	MOMIP	×	✓	×	×
[38]	Malaysia	✓	×	×	MINLP	×	✓	×	×
[39]	India	✓	×	×	MILP	×	✓	×	×
[40]	Vietnam	✓	✓	×	MINLP	×	✓	×	×
[41]	Malaysia	✓	×	×	MILP	×	✓	×	✓
[42]	Malaysia	✓	✓	×	MILP	×	✓	×	✓
[43]	UAE	✓	✓	×	MOMILPM	✓	✓	×	✓
[44]	Malaysia	✓	✓	×	MOLP	×	✓	×	✓
[45]	Tehran	✓	✓	×	MOOP	×	×	✓	×
[46]	Tehran	✓	✓	✓	MOOP	✓	✓	×	✓
[47]	China	✓	✓	×	MOMLP	✓	✓	×	×
[48]	NA	✓	×	×	MOOP	✓	×	✓	×
[49]	NA	✓	✓	×	MOOP	×	×	✓	×
Current work	India	✓	✓	✓	MOMLSTM	✓	✓	✓	✓

MINLP: Mixed integer non-linear programming, MILP: Mixed integer linear programming, LP: Linear programming, MOOP: Multi-objective optimization problem, MOMLP: Multi-objective multi-level problem, MOMILPM: Multi-objective multi-integer linear programming problem, MOMLSTM: Multi-objective multi-level solid transportation problem, NA: Not available

The ineffectiveness of bio capping in landfill rehabilitation can be attributed to several factors:

- Time-consuming procedure: For post-closure upkeep to track contaminants in the soil, surface-water avenues, and the atmosphere, a minimum of fifteen years of monitoring is necessary.
- Frequent assessment: Frequent assessment of settling of landfill due to leachate production, sedimentation, and organic encroachment by plants.
- Contrarily, biomining-based landfill cleanup guarantees long-lasting and ecologically appropriate handling of accumulated waste. Additionally, profitable revenue-yielding potential is provided by biomining enterprises. Biomining is majorly a six-step process as described below:
  - Pre-feasibility analysis, which includes comprehensive examinations of the location, research, and trash characterization
  - Meticulous removal of old waste
  - Decreasing the overall weight and scale of the trash by consolidation using bio inoculum;
  - Treatment of the dug-up portion
  - Employing recovered waste components in a variety of profitable scenarios
  - Tidying up and preparing reclaimed land

The multiple-step biomining process must be profit inclined in order to achieve higher adaptability across various dumpsite biomining projects. The formulation of an optimization framework for biomining, which is sustainable and profit-yielding, is developed in this paper.

The proposed mathematical model is highly efficacious and sustainable as it incorporates three crucial objectives of any successful business framework, i.e., profit, sustainability, and time. The functioning and outcomes of the model provided in this study are affected by several uncertainties and unanticipated events. The magnitude of the pollution generated by landfills on the ground, air, and water bodies is very ambiguous, which has an influence on the different costs connected with redemption. These are only a few of the potential uncertainties that may be encountered by this model. Technology restrictions raise uncertainty even further. Excavation of landfills is subject to complicated legal requirements and norms, which might result in delays and increased costs. Societal acceptability is another significant factor in uncertainty since, in many places of the world, landfill excavation uproots the livelihood of nearby residents. Finally, the market's need for land that had been repurposed increased uncertainty. The parameters are assumed to be pentagonal neutrosophic numbers in order to account for this ambiguity.

III. MATHEMATICAL MODEL FORMULATION

The elaboration of the mathematical model explaining the various sets and indices, as well as the many notations that were utilized to build the model, is provided in this part. Additionally, it defines each component associated with three objective functions and every constraint that was created in order to optimize the model's objectives, model interpretation is a crucial part of this section.

A. ASSUMPTIONS FOR THE MODEL

- Waste separation and segregation takes place at the processing site itself.
- Landfill holds both legacy and fresh municipal waste.
- The potential location of processing plants is known beforehand.
- Biomining procedure is implemented for landfill redemption.
- Cost of rehabilitation of landfill post clearing is not included.
- The MOMLSTM represents unbalanced transportation problem.

B. INDICES

- I: set of landfill sites indexed by i
- J: set of waste processing plants indexed by j.
- K: set of conveyances used to transport waste from landfill to processing plant indexed by k.
- K' : set of conveyances used to transport waste from processing plant to demand point indexed by k'.
- M: set of prospective demand locations of new-value added products attained post-processing indexed by m.
- L: set of various type of new-value added products produced from landfill waste post biomining procedure.

C. PARAMETERS

- $\widetilde{\mathrm{PFS}}$: Fuzzy cost of pre-feasibility study of waste lying at landfill per volume unit
- $\widetilde{\mathrm{DCC}}$: Fuzzy data collection cost from landfill per volume unit
- $\widetilde{\mathrm{LT}}$: Fuzzy laboratory testing cost of landfill waste per unit volume
- $\widetilde{\mathrm{BIP}}$: Bio inoculum procurement cost in fuzzy involving the purchasing cost of bio inoculum required for each unit of waste
- $\widetilde{\mathrm{LCB}}$: Labor cost of spraying bio inoculum over per unit volume waste in fuzzy number.
- $\widetilde{\mathrm{SED}}$: Fuzzy cost of systematic excavation of dumpsite per volume unit
- $\widetilde{\mathrm{SPC}}$: Site preparation cost for excavation over per unit volume waste as fuzzy number
- $\widetilde{\mathrm{EQC}}$: Equipment cost for excavation over per unit volume waste as fuzzy number
- $\widetilde{\mathrm{LAO}}$: Labor and administrative overhead cost during excavation over per unit volume waste as fuzzy number
- $\widetilde{\mathrm{SBI}}$: Fuzzy cost of spraying of bio inoculum in order to reduce mass of waste per volume unit
- $\widetilde{\mathrm{TC}}_{ijk}$: Fuzzy cost of transporting per unit volume waste from landfill (i) to processing plant (j) using vehicle (k) .
- $\widetilde{\mathrm{CC}}_{ijk}$: Fuzzy cost of process of waste collection at landfill (i) being sent to processing plant (j) using vehicle (k) per unit volume
- $\widetilde{\mathrm{SS}}_{ij}$: Fuzzy cost of sorting and segregation of per unit volume of waste at processing plant (j) arriving from landfill (i)
- $\widetilde{\mathrm{PRF}}$: Average price of new value-added products generated from unit volume waste from landfill in fuzzy
- $\widetilde{\mathrm{PP}}_{ij}$: Fuzzy cost of processing waste to attain new value-added product at processing plant (j) arriving from landfill (i) per unit volume
- $\widetilde{\mathrm{I}}_{jl}$: Fuzzy inventory cost of per unit volume product arriving from processing plant (j) to demand point (l)
- $\widetilde{\mathrm{TCT}}_{jmk'}$: Fuzzy cost of transporting per unit volume of value-added product from processing plant (j) to demand point (m) using vehicle (k')
- $\widetilde{\mathrm{CL}}$ Fuzzy amount of carbon emitted from per unit volume waste lying at landfill
- $\widetilde{\mathrm{CAD}}$: Fuzzy quantity of methane resulting from the anaerobic breakdown of organic waste per unit volume of waste present at the landfill
- $\widetilde{\mathrm{CAM}}$: The imprecise quantity of carbon dioxide resulting from waste combustion or microbial respiration per unit volume of waste deposited in a landfill
- $\widetilde{\mathrm{CAV}}$: The imprecise quantity of volatile organic compounds originating from specific waste types or microbial respiration within each unit volume of waste deposited in a landfill
- $\widetilde{\mathrm{CAN}}$: The fuzzy quantity of nitrous oxide produced from the incineration of waste containing nitrogen within each unit volume of waste present in the landfill
- $\widetilde{\mathrm{CE}}$ Fuzzy amount of carbon emitted by vehicles responsible for excavation of waste at landfills per unit volume
- $\widetilde{\mathrm{CT}}_{ijk}$: Fuzzy amount of carbon emitted in transporting per unit volume waste from landfill (i) to processing plant (j) using vehicle (k)

- $\widetilde{\mathrm{CP}}_j$: Fuzzy amount of carbon emitted by machinery while processing per unit volume of waste at processing plant (j)
- $\widetilde{\mathrm{CS}}_j$: Fuzzy amount of carbon emitted per unit volume of waste by sorting and segregation plant at processing plant (j)
- $\widetilde{\mathrm{CI}}_{jl}$: Fuzzy amount of carbon emission due to usage of electricity at inventory situated in processing plant (j) for storage of value-added product (l)
- $\widetilde{\mathrm{CTT}}_{jmk'}$: Fuzzy amount of carbon emission per unit volume of value-added product from processing plant (j) to demand point (m) using vehicle (k')
- $\widetilde{\mathrm{TPF}}$: Time taken in fuzzy pre-feasibility study of waste lying at landfill per volume unit
- $\widetilde{\mathrm{TED}}$ Time taken in fuzzy for systematic excavation of dumpsite per volume unit
- $\widetilde{\mathrm{TSB}}$ Time taken in fuzzy for spraying of bio inoculum in order to reduce mass of waste per volume unit
- $\widetilde{\mathrm{TSS}}_j$: Time taken as fuzzy in sorting and segregation of per unit volume of waste at processing plant (j)
- $\widetilde{\mathrm{TPP}}_{ij}$: Time taken as fuzzy for processing waste to attain new value-added product at processing plant (j) arriving from landfill (i)
- $\widetilde{\mathrm{TT}}_{ijk}$: Time taken as fuzzy during of transportation waste from landfill (i) to processing plant (j) using vehicle (k)
- $\widetilde{\mathrm{TTT}}_{jmk'}$: Time taken as fuzzy during of transportation of value-added product from processing plant (j) using vehicle (k) to demand point (m) using vehicle (k')
- $\widetilde{a}_i$: Maximum waste holding capacity of landfill (i) in fuzzy
- $\widetilde{b}_j$: Maximum waste holding capacity of processing plant (j) in fuzzy
- $\widetilde{c}_k$: Waste holding capacity in fuzzy of vehicle transporting from landfill to processing plant
- $\widetilde{A}_{jl}$: value-added product (i) holding capacity in fuzzy of inventory at processing plant (j)
- $\widetilde{\mathrm{DP}}_j$: Minimum waste assigning limit for processing plant (j) in fuzzy
- $\widetilde{B}_{ml}$: Requirement of value-added product (l) at demand point (m) in fuzzy
- $\widetilde{V}_{k'}$: Capacity of vehicle transporting from processing plant to demand point
- $\widetilde{\mathrm{CCL}}_i$: Carbon cap at landfill (i) in fuzzy
- $\widetilde{\mathrm{CCT}}$: Carbon cap across the entire transportation in fuzzy
- $\widetilde{\mathrm{CCP}}_j$: Carbon cap at processing site (j) in fuzzy
- $\widetilde{\mathrm{TB}}$: Time bound for the entire landfill clearing process

D. DECISION VARIABLES

- x_{ijk}: Volume of waste transported from landfill (i) to processing plant (j) using vehicle (k)
- $x_{jmk'l}$: Volume of value-added product (l) transported from processing plant (j) using vehicle (k) to demand point (m) using vehicle (k')
- $\rho_{ijjk}: \begin{cases} 1, & \text{if } x_{ijk} > 0 \\ 0, & otherwise \end{cases}$
- $\rho_{jmk'l}: \begin{cases} 1, & \text{if } x_{jmk'l} > 0 \\ 0, & otherwise \end{cases}$

E. MULTI-OBJECTIVE MULTI-LEVEL SOLID TRANSPORTATON MODEL

$$\begin{aligned} \mathrm{MaxProfit} &= \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\mathrm{PRF}\left(x_{ijk}\right) \\ &- \Big\{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\big(\widetilde{\mathrm{PFS}}+\widetilde{\mathrm{SED}}+\widetilde{\mathrm{CC}}_{ijk}+\widetilde{\mathrm{TC}}_{ijk} \\ &+\widetilde{\mathrm{SS}}_{ij}+\widetilde{\mathrm{PP}}_{ij}\big)\,x_{ijk}+\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{k'=1}^{K'}\sum_{l=1}^{L} \\ &\big(\widetilde{I}_{jl}+\widetilde{\mathrm{TCT}}_{jmk'}\big)\,x_{jmk'l}\Big\} \end{aligned} \tag{1}$$

$$\begin{aligned} Min\ CE &= \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\big(\widetilde{\mathrm{CL}}+\widetilde{\mathrm{CE}}+\widetilde{\mathrm{CT}}_{ijk}+\widetilde{\mathrm{CS}}_j \\ &+\widetilde{\mathrm{CP}}_j\big)\,x_{ijk}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{k'=1}^{K'}\sum_{l=1}^{L}\big(\widetilde{\mathrm{CI}}_{jl}+\widetilde{\mathrm{CTT}}_{jmk'}\big) \\ &\times x_{jmk'l} \end{aligned} \tag{2}$$

$$\begin{aligned} Min\ Time &= \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\big(\widetilde{\mathrm{TPF}}+\widetilde{\mathrm{TED}}+\widetilde{\mathrm{TSB}} \\ &+\widetilde{\mathrm{TSS}}_j+\widetilde{\mathrm{TPP}}_{ij}\big)\,x_{ijk}+\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\big(\widetilde{\mathrm{TT}}_{ijk}\big)\,\rho_{ijjk} \\ &+\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{k'=1}^{K'}\sum_{l=1}^{L}\big(\widetilde{\mathrm{TTT}}_{jmk'}\big)\,\rho_{jmk'l} \end{aligned} \tag{3}$$

$$\sum_{j=1}^{J}\sum_{k=1}^{K}x_{ijk}\le\widetilde{a}_i \tag{4}$$

$$\sum_{i=1}^{I}\sum_{k=1}^{K}x_{ijk}\le\widetilde{b}_j \tag{5}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}x_{ijk}\le\widetilde{c}_k \tag{6}$$

$$\sum_{i=1}^{I}\sum_{k=1}^{K}x_{ijk}\ge\widetilde{\mathrm{DP}}_j \tag{7}$$

$$\sum_{j=1}^{J}\sum_{l=1}^{L}x_{jmk'l}\le\widetilde{A}_{jl} \tag{8}$$

$$\sum_{j=1}^{J}\sum_{k'=1}^{K'}x_{jmk'l}\ge\widetilde{B}_{ml} \tag{9}$$

$$\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{l=1}^{L}x_{jmk'l}\le\widetilde{V}_{k'} \tag{10}$$

$$\sum_{j=1}^{J}\sum_{k=1}^{K}x_{ijk}\le\widetilde{\mathrm{CCL}}_i \tag{11}$$

$$\begin{aligned} &\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\big(\widetilde{\mathrm{CT}}_{ijk}\big)\,x_{ijk}+\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{k'=1}^{K'} \\ &\quad\sum_{l=1}^{L}\big(\widetilde{\mathrm{CTT}}_{jmk'}\big)\,x_{jmk'l}\le\widetilde{\mathrm{CCT}} \end{aligned} \tag{12}$$

$$\begin{aligned} &\sum_{i=1}^{I}\sum_{k=1}^{K}\big(\widetilde{\mathrm{CS}}_j+\widetilde{\mathrm{CP}}_j\big)\,x_{ijk}+\sum_{m=1}^{M}\sum_{k'=1}^{K'}\sum_{l=1}^{L} \\ &\quad\times\big(\widetilde{\mathrm{CI}}_{jl}\big)\,x_{jmk'l}\le\widetilde{\mathrm{CCP}}_j \end{aligned} \tag{13}$$

$$\begin{aligned} &\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\big(\widetilde{\mathrm{TPF}}+\widetilde{\mathrm{TED}}+\widetilde{\mathrm{TSB}}+\widetilde{\mathrm{TSS}}_j+\widetilde{\mathrm{TPP}}_{ij}\big) \\ &\quad\times x_{ijk}+\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\big(\widetilde{\mathrm{TT}}_{ijk}\big)\,\rho_{ijjk} \\ &\quad+\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{k'=1}^{K'}\sum_{l=1}^{L}\big(\widetilde{\mathrm{TTT}}_{jmk'}\big)\,\rho_{jmk'l}\le\widetilde{\mathrm{TB}} \end{aligned} \tag{14}$$

F. INTERPRETATION OF MODEL

A viable model regarding landfill restoration is demonstrated by the mathematical model discussed in sub-section E of section III. Since landfill restoration is expensive, time-consuming, and generates carbon during operation, the main goal of any company that engages in this sector is to maximize profit while minimizing both carbon emissions and time as formulated in objectives (1), (2), and (3) respectively. Pre-feasibility analysis is the initial phase in the biomining technology employed for landfill rehabilitation. This assessment's objective is to analyze every pertinent dependency, including time-sensitive, fiscal, and technological ones. The cost of this assessment is captured by parameter $\left(\widetilde{\mathrm{PFS}}\right)$. The expenses associated with conducting a prefeasibility analysis can be divided into two main components: the cost of data collection $(\widetilde{\mathrm{DCC}})$, which encompasses site surveys, field measurements, and data logging; and the cost incurred within laboratories $(\widetilde{\mathrm{LT}})$. The laboratory costs include expenditures related to equipment, data analysis, quality control, and report generation, all of which are incurred after the collection of waste samples. Thus, $\widetilde{\mathrm{PFS}} = \widetilde{\mathrm{DCC}} + \widetilde{\mathrm{LT}}$. The tedious and expensive process of excavating garbage from landfills includes the cost of creating an operation plan, purchasing safety gear, controlling fires, hiring trained staff, purchasing effective equipment, and managing odors resulting from leachates. The entire cost of excavation is denoted by $\left(\widetilde{\mathrm{SED}}\right)$. The total excavation cost can be categorized into three primary components: site preparation cost $(\widetilde{\mathrm{SPC}})$, which covers activities like site clearing, permit acquisition, and erosion control; equipment expenses $(\widetilde{\mathrm{EQC}})$, encompassing fuel and maintenance costs; and labor and administrative expenses incurred throughout the excavation process $(\widetilde{\mathrm{LAO}})$. Consequently, the deconstructed excavation cost can be represented as $\left(\widetilde{\mathrm{SED}}\right) = (\widetilde{\mathrm{SPC}}) + \left(\widetilde{\mathrm{EQC}}\right) + (\widetilde{\mathrm{LAO}})$. The compostable portion of legacy trash in microbe-mediated stabilization breaks down, lowering its bulk and dimension. For the purpose of reducing insects, eradicating infectious activity, reducing moisture, and completing the procedure of biodegradation, the waste site is stabilized by converting it into rows of similar size in a systematic way. Bio inoculum is used for this purpose. The cost of spraying bio inoculum is denoted by $\left(\widetilde{\mathrm{SBI}}\right)$. It is possible to divide the main expenses related to applying bio-inoculum into two main parts. First, there is the cost of obtaining the bio-inoculum itself $(\widetilde{\mathrm{BIP}})$, which includes the expenses incurred in obtaining it from outside sources or creating it internally. The second factor is the labor cost involved in spraying the bio-inoculum $(\widetilde{\mathrm{LCB}})$. Wages for the labor force in charge of the application are included in these labor costs, together with charges for maintaining their safety and adherence to applicable laws. Therefore, mathematically $\widetilde{\mathrm{SBI}} = \widetilde{\mathrm{BIP}} + \widetilde{\mathrm{LCB}}$. At the processing facility, the material is separated using a variety of techniques, including ferrous separation, screening, shredding, and air classification, and it is screened mostly according to its size. Cost of this is denoted by $\left(\widetilde{\mathrm{SS}}_{ij}\right)$. Following segregation, processing is performed to produce new products with additional value which can potentially be deployed for a variety of purposes, including soil enrichment, RDF and road building, clay replacement in the construction sector, and road-building. Cost of this is denoted by $\left(\widetilde{\mathrm{PP}}_{ij}\right)$. Apart from this the other important considered while maximizing profit in equation (1) are inventory cost $\left(\widetilde{I}_{jl}\right)$, waste collection cost $\left(\widetilde{\mathrm{CC}}_{ijk}\right)$, and transportation cost $\left(\widetilde{\mathrm{TC}}_{ijk}, \widetilde{\mathrm{TCT}}_{jmk'}\right)$.

Objective 2 deals with minimizing carbon emission. It takes into consideration the carbon emission from waste lying in landfill $\left(\widetilde{\mathrm{CL}}\right)$ as this waste generates methane, and other highly potent GHGs. A vast variety of trash coexist in landfills, creating intricate ecological systems that encourage the production of different GHGs. To go into more detail, a significant supplier of methane gas (CH4), a powerful greenhouse gas, is the breakdown of organic waste in anaerobic environments $(\widetilde{\mathrm{CAD}})$. Additionally, carbon dioxide (CO2), another important GHG, is released during the process of waste combustion $(\widetilde{\mathrm{CAM}})$ or microbial respiration. Moreover, certain waste kinds may release volatile organic chemicals $(\widetilde{\mathrm{CAV}})$, which may have a variety of negative effects on the environment. Additionally, burning nitrogen-containing trash produces nitrous oxide $(\widetilde{\mathrm{CAN}})$ which increases greenhouse gas emissions. Thus, the overall emission from waste lying in landfill can be broken down as $\widetilde{\mathrm{CL}} = \widetilde{\mathrm{CAD}} + \widetilde{\mathrm{CAM}} + \widetilde{\mathrm{CAV}} + \widetilde{\mathrm{CAN}}$. This range of greenhouse gases produced by garbage highlights how crucial it is to comprehend and control landfill emissions in order to lessen their negative effects on the environment and support environmentally friendly waste management techniques. Emission from equipment and vehicles $\left(\widetilde{\mathrm{CE}}\right)$ used for excavation is also captured. Waste segregation $\left(\widetilde{\mathrm{CS}}_j\right)$ and processing $\left(\widetilde{\mathrm{CP}}_j\right)$ is an intricate process that requires complicated machinery which further adds to carbon emission. The value-added products attained post processing plant are stored in inventory and the carbon emission from inventory is captured with $\left(\widetilde{\mathrm{CI}}_{jl}\right)$. Vehicle carrying waste from landfill to processing plant and from there to demand points contribute to carbon emission and are captured using $\left(\widetilde{\mathrm{CT}}_{ijk}\right)$ and $\left(\widetilde{\mathrm{CTT}}_{jmk'}\right)$. Landfill redemption projects comes with strict timelines, thus minimizing time is one of the most crucial targets for this process. Objective (3) deals with this issue, the predominant time-consuming process like prefeasibility study $\left(\widetilde{\mathrm{TPF}}\right)$, systematic excavation $\left(\widetilde{\mathrm{TED}}\right)$, bio-inoculum spraying $\left(\widetilde{\mathrm{TSB}}\right)$, sorting of waste $\left(\widetilde{\mathrm{TSS}}_j\right)$, processing of sorted waste $\left(\widetilde{\mathrm{TPP}}_{ij}\right)$, and transportation of waste $\left(\widetilde{\mathrm{TT}}_{ijk}\right)$ and new value aaded products $\left(\widetilde{\mathrm{TTT}}_{jmk'}\right)$ are covered in this objective.

Constrain (4) is responsible for putting a check on the quantity of waste being transported from landfill (i) to processing plant (j) using the vehicle (k); it makes sure that the quantity of waste transported cannot be more than the waste available at the landfill (i). Constraint (5) makes sure that processing plant (j) capacity is not exploited. No compromise is made in transportation by misusing the weight holding capacity of vehicles is made sure by constraints (6) and (10). For proper utilization of resources, there is a minimum limit of waste that must be assigned to each processing center which is made sure by constraint (7). Inventory capacity is checked by constraint (8). The requirement of each demand point is fulfilled is made sure by constraint (9). Constraint (11) is responsible for putting a carbon cap at the processing site. Carbon cap for the entire transportation procedure is implemented by constraint (14). Constraint (15) is responsible for putting a time bound on the landfill redemption process.

IV. PRELIMINARY CONCEPTS OF FUZZY USED IN FORMULATION OF MATHEMATICAL MODEL

The following subsections contain details on the fuzzy concepts that are employed to represent uncertainty in the landfill redemption model outlined in section III. Considering that numerous external variables play a significant role in the landfill reclamation procedure, the parameters associated with the mathematical model cannot be taken as exact values. The use of pentagonal fuzzy numbers as parameters allows for the resolution of this issue. Following are definitions of pentagonal fuzzy numbers and a description of the defuzzification procedure:

A. PENTAGONAL FUZZY NUMBER

A pentagonal fuzzy number represented by $\widetilde{p} = (p_1, p_2, p_3, p_4, p_5, g)$ and the corresponding membership function $\mu_{\widetilde{p}}(z)$ need to satisfy following conditions [50]:

- In the interval $[0, 1]$ the membership function $\mu_{\widetilde{p}}(z)$ should be continuous
- The function $\mu_{\widetilde{p}}(z)$ should be non-decreasing in the interval $[p_1, p_2]$ and $[p_2, p_3]$
- The function $\mu_{\widetilde{p}}(z)$ should be non-increasing in the interval $[p_3, p_4]$ and $[p_4, p_5]$

Definition of membership function for PFN is as follows:

$$\mu_{\widetilde{p}}(z) = \begin{cases} 0 \;\; if \;\; z \leq p_1 or \; z \geq p_5 \\ g\dfrac{z-p_1}{p_2-p_1} \;\; if \;\; p_1 \leq z \leq p_2 \\ g + (1-g)\,\dfrac{z-p_1}{p_2-p_1} \;\; if \;\; p_2 \leq z \leq p_3 \\ 1 \;\; if \;\; z = p_3 \\ g + (1-g)\,\dfrac{p_4-z}{p_4-p_3} \;\; if \;\; p_3 \leq z \leq p_4 \\ g\dfrac{p_5-z}{p_5-p_4} \;\; if \;\; p_4 \leq z \leq p_5 \end{cases}$$

B. DEFUZZIFICATION TECHNIQUE FOR PENTAGONAL FUZZY NUMBER

Fuzzy parameters are incapable of being employed directly for a multitude of causes, including decision-making, human comprehension, integration into conventional control mechanisms, streamlining of results, and comparative evaluation. Thus, the defuzzification approach, also known as the crisp conversion method, is required. For defuzzification of PFN $(\widetilde{p})$ it is disintegrated into one rectangular region and three triangular regions as shown in Figure 2. The crisp form is evaluated as the value of centroid of PFN $(\widetilde{p})$ as shown below [51]:

$$C = \frac{\sum_{i=1}^{4} \Psi_i \times \Phi_i}{\sum_{i=1}^{4} \Phi_i} = \frac{\Psi_1 \times \Phi_1 + \Psi_2 \times \Phi_2 + \Psi_3 \times \Phi_3 + \Psi_4 \times \Phi_4}{\Phi_1 + \Phi_2 + \Phi_3 + \Phi_4}$$

$$\text{centroid of decomposed shape 1 } (\Psi_1) = \frac{p_1 + 2p_2}{3}$$

$$\text{centroid of decomposed shape 2 } (\Psi_2) = \frac{p_2 + p_3 + p_4}{3}$$

$$\text{centroid of decomposed shape 3 } (\Psi_3) = \frac{2p_4 + p_5}{3}$$

$$\text{centroid of decomposed shape 4 } (\Psi_4) = \frac{p_2 + p_4}{2}$$

$$\text{Area of decomposed shape 1 } (\Phi_1) = (p_2 - p_1)\,\frac{g}{2}$$

$$\text{Area of decomposed shape 2 } (\Phi_2) = (p_4 - p_2)\,\frac{(1-g)}{2}$$

$$\text{Area of decomposed shape 3 } (\Phi_3) = (p_5 - p_4)\,\frac{g}{2}$$

$$\text{Area of decomposed shape 4 } (\Phi_4) = (p_4 - p_2)\,g$$

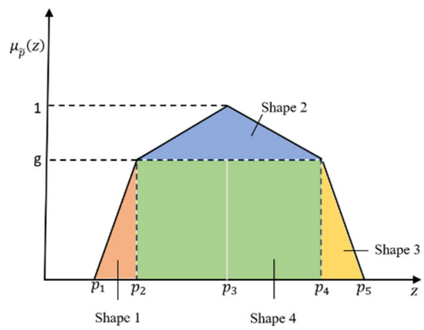


FIGURE 2. Disintegrated pentagonal fuzzy number.

V. PROPOSED ALGORITHM FOR SOLVING THE MOMLSTM: GENETIC ALGORITHM WITH OFFSPRING REFINEMENT (GAOR)

The current problem examined in this paper encompasses three contradictory objectives to be optimized during landfill excavation and management. It is an NP-hard problem. Achieving the optimal solution of an NP-hard problem is challenging as it has high time and space complexity. That is where GA come to the rescue. It is a method that is inspired by natural genetics in charge of the dynamics of biological evolution and is a stochastic and heuristic search method. It has already proven its performance in solving STP in the past. Utilization of GA in attaining optimal results for STP was first niched by [52]. However, GA proposed here is an upgraded version of the traditional GA; it involves augmentation of offspring refinement step post mutation. This section holds all relevant information on various methods and parameters involved during crossover and mutation steps, along with other steps of GA like chromosome representation, population initialization, fitness function etc., as shown below:

- Chromosome representation: Chromosome is one of the candidates for solution. Here, it is representation of transportation scheme. It comprises of several genes which are nothing but decision variables. The model considered in this work engages two kind of decision variables. Thus, for the sake of detailed representation of chromosome it is bifurcated into two sub-chromosomes. The first kind of sub-chromosomes for decision variable from landfill to processing site (SC-LP); it holds information of the decision variables responsible in transportation from landfill to processing plant. Second kind of sub-chromosomes i.e., sub-chromosomes for decision variable from processing site to demand point (SC-PD). The two types of sub-chromosomes are shown in fig. 3. Sub-chromosome SC-LP and SC-PD clasps all the genes of form x_{ijk} and $x_{jmk'l}$ respectively.
- *Population initialization and size:* Population initialization and size are two important parameters that play an indispensable role in GA. The goal of the initialization step is to impart a diversified and representative beginning population that will be utilized in the next stages of evolution. Random initialization technique is a widely used technique for initialization [53]. It is a strategy that is frequently used and involves initializing the population with completely random solutions. By presenting a wide variety of starting solutions, this strategy seeks to increase solution heterogeneity. Algorithm 1 demonstrates the utilization of this approach in the current context. Population size is responsible for the exploration and exploitation of solution space; the quality of the solution depends on it. There is always a trade-off in computational resources and diversity while choosing population size. The final pick of population size for this work was done using from Taguchi experiment.
- *Parent selection:* Parent selection is a crucial step in GA. The principal outcome of this step leads to the election of parents from the population to create better offspring. Identifying parents that possess "excellent" genes enables those traits to be carried down through the subsequent generations. The overall convergence pace of a GA depends heavily on choosing parents since effective parents encourage individuals to find more appropriate and superior solutions. Here, five parent selection operators are considered that are as follows [54]:
  - Stochastic Universal Sampling
  - Tournament Selection
  - The truncation selection
  - Roulette Wheel Selection
  - Rank selection method

By removing any prejudice in favor of individuals who have elevated fitness levels and raising the selection stress, stochastic universal sampling outperforms the conventional fitness proportional selection. The following is accomplished by uniformly distributing the points across the roulette wheel, which increases the likelihood that those with greater levels of fitness will be picked more than once. In the tournament selection method, the most outstanding individuals are picked to serve as the parents of the following generation after holding "tournaments" amongst arbitrarily selected members of the population. The selection process used in tournaments strikes a compromise between selection stress and variety conservation. Whereas the next selection technique i.e., truncation selection technique, entails choosing a specified percentage of the population's top individuals in accordance with their fitness ratings as parents. Next is the roulette wheel selection approach. It involves creating a roulette wheel featuring parts that are proportionate to the likelihood of every individual being chosen. The dimension of the various parts on the wheel, which has been split into sections, reflects how likely an individual is to be chosen. In the rank selection technique, tanks are assigned to the individuals base on their output from fitness function. Later selection probability comes into the picture which is calculated using the normalizing factor and rank of an individual.

Algorithm 1 Algorithm for Random Initialization

Input: $a_i, b_j, c_k, A_{jl}, B_{ml}, v_{k'}$
Output:
$O_1 = \{x_{111}, \ldots, x_{ijk}\}, O_2 = \{x_{1111}, \ldots, x_{jmk'l}\}$
count $= I * J * K * M * K' * L$
While (*count* $\neq \emptyset$) do
  Select arbitrary number Ψ *from set count*;
  Computing indices of decision variables;
  $i = (count - 1)\, mod\, (I + 1)$;
  $j = [(count - 1)/I] mod\, (J + 1)$;
  $k = [(count - 1)/(I * J)] mod\, (J + 1)$;
  $m = [(count - 1)/(I * J * K)] mod\, (J + 1)$;
  $k' = [(count - 1)/(I * J * K * M)] mod\, (J + 1)$;
  $l = [(count - 1)/I * J * K * M * K'] mod\, (J + 1)$;
  Data assignment;
  $x_{ijk} = \{\min a_i, b_j, c_k\}$;
  $x_{jmk'l} = \{\min A_{jl}, B_{ml}, v_{k'}\}$;
  Data updating;
  $a_i = x_{ijk} - a_i$;
  $b_j = x_{ijk} - b_j$;
  $c_k = x_{ijk} - c_k$;
  $A_{jl} = x_{jmk'l} - a_i$;
  $B_{ml} = x_{jmk'l} - b_j$;
  $v_{k'} = x_{jmk'l} - v_{k'}$;
end
  Return O_1 *and* O_2;

- *Fitness function:* A particular solution's "fitness" amongst an overall population is assessed using a fitness function in a GA. How effectively an individual accomplishes the targeted assignment or achieves, the goals of the problem being addressed is determined by their fitness function. The population's growth through generations that follow is subsequently guided by the algorithm using this evaluation. The various alternatives for fitness function selection are established on scenarios like objective-based fitness, optimizing resource fitness, classification accuracy, simulation-based matrices, and constraint satisfaction. Here, the objective of the model being solved is clear; thus objective-based fitness function is implemented. This fitness function takes care of the following traits of the solution measure of quality, criteria of optimization, fitness scaling, fitness evaluation, and fitness proportion. To attain a fitness function dealing with all three objectives of the model, the compromise programming technique game theory approach is availed [55].

- *Crossover:* In order to produce superior offspring, recombination of genetic information between two chromosomes is accomplished through crossover, an essential stage in GA. It oversees producing numerous combinations of children from two selected parents. Based on their operational mechanism, crossover come in a variety of forms. Some of the frequently used crossovers involve one-point crossover under this variant of crossover, random selection of a point is initiated, which is later referred as crossover point. At this designated point, the genetic information located beyond it is exchanged between the parents, resulting in the creation of offspring individuals. This crossover provides genetic variety and may result in novel trait combinations in the progeny [56]. Next is two-point crossover it is an upgraded version of a one-point crossover. It identifies two crossover spots within each parent chromosome and switches the genetic information across the parents with these two points as the frame of reference. Comparatively, this crossover approach tends to have higher diversity, it promotes greater variation and makes it easier to experiment with different genetic arrangements by allowing genetic material to move between two designated sites [56]. Uniform crossover facilitates an additional random and distinct transmission of genetic data. It facilitates the blending of genetic data at the distinct levels of genes, opening the possibility of exploring numerous combinations. Under cycle crossover, the underlying cycle of chromosome is first identified. The underlying chromosome cycles are first identified via the cycle crossover operator. The initial location in the first parent is chosen arbitrarily, while the cycle is subsequently traced through locating the matching components of the subsequent parent and noting visited elements. Up till all constituents are a member of a cycle, that procedure is recurred. Using the recognized cycles, the genetic code from the parent chromosomes is alternately copied to form the next generation of individuals. It permits the retention of certain patterns present in the parent's chromosomes, encouraging the investigation of related approaches during the subsequent generation process [56]. Apart from crossover operation, the other important factor responsible for crossover is the probability of crossover. This parameter controls the possibility or probability of implementing crossover onto an assortment of parent individuals in GA. In a GA, the crossover probability aids in striking the right equilibrium between exploration and extraction. Former is encouraged by a larger crossover probability, which raises the likelihood of reassembling genetic information. This may aid the algorithm's search for fresh, possibly superior solutions. The latter is favored by lower crossover probability by conserving more genetic information. However, the determination of the appropriate crossover type and crossover probability depends largely on the problem being solved. Thus, the Taguchi method is employed to calculate the best-fit parameter setting for the GA being used here. The S/N ratio table implies that a two-point crossover is the best fit for the current GA, as shown in Figure 9 and Table 10 and 11. The working of two-pint crossover is shown in Figure 4 and 5.

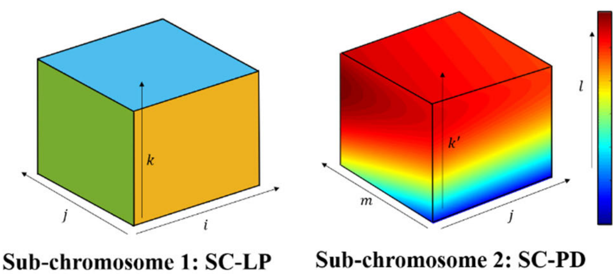


FIGURE 3. Pictorial representation of the two sub-chromosomes of MOMLSTM.

Apart from crossover operation, the other important factor responsible for crossover is the probability of crossover. This parameter controls the possibility or probability of implementing crossover onto an assortment of parent individuals in GA. In a GA, the crossover probability aids in striking the right equilibrium between exploration and extraction. Former is encouraged by a larger crossover probability, which raises the likelihood of reassembling genetic information. This may aid the algorithm's search for fresh, possibly superior solutions. The latter is favored by lower crossover probability by conserving more genetic information. However, the determination of the appropriate crossover type and crossover probability depends largely on the problem being solved. Thus, the Taguchi method is employed to calculate the best-fit parameter setting for the GA being used here. The S/N ratio table implies that a two-point crossover is the best fit for the current GA, as shown in Figure 9 and Table 10 and 11. The working of two-pint crossover is shown in Figure 4 and 5.

- *Mutation:* A key component of GA is mutation. After crossover, the GA process advances with this step. With this technique, chromosomal alterations are performed at the gene level. In addition to allowing the procedure to investigate novel areas of the solution space, mutation contributes to preserving genetic variety. It serves as an exploration technique that enables the GA to leave its immediate vicinity of local optima and discover fresh

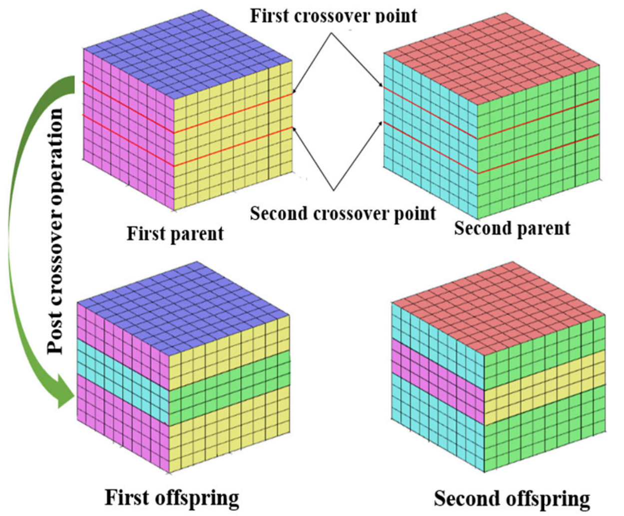


FIGURE 4. Two-point crossover mechanism in sub-chromosome SC-LP.

areas of the solution space. The individuals chosen for mutation are entirely based on the probability of mutation. Based on the likelihood of mutation, participants are selected for mutation. It regulates how frequently or quickly a population's members experience mutation. It shows the possibility that a gene or chromosomal segment will change throughout the algorithm's reproduction phase. The right mutation chance relies on the issue, the structure of the population at large, and how additional GA operators, such as the crossover phenomenon, interact with it. There are many different mutation processes, and the one selected depends on the issue. Based on the Taguchi experiment's calculation performed in Figure 8 and Table 10 and 11, the best-fit mutation is an Inversion mutation for the current problem; it is working, is shown in Figure 6. Some frequent mutations in GA include the following,under inversion mutation a subset of the chromosomes, or a handful of genes, are picked arbitrarily after chromosomes are picked depending on what score they achieve in the fitness function. The chosen subpart's sequence is inverted in order to find the mutated individual, who is then carefully reintroduced into the population. Parameter tuning of parameters like the subset size can further enhance the functionality of this operator [54]. By assisting GA in overcoming stasis and pursuing alternate routes in the hunt for better answers, it serves as a means of escaping local optima. Next is swap mutation, GA frequently employ the mutation operator known as swap mutation. It entails picking a pair of genes arbitrarily from the chromosome and switching their locations to produce a new individual. Random selection determines which two different genes on a chromosome will be switched. The genes can be selected according to any chromosomal location. The chromosome locations of the chosen genes are switched [57]. It suggests that the features or characteristics that those genes stand for have been flipped around. The picked genes are replaced with those in reversed locations to produce a transformed individual. This can prompt the investigation of related solutions and prospective upgrades in the pursuit of superior ones. Another important mutation is insertion mutation, by arbitrarily picking a gene from a chromosome and moving it to a fresh site, an insertion mutation results in a mutant individual possessing a changed genetic profile. In this experiment, a gene is picked at independently for the incision following individuals have been chosen according to fitness function. The chosen gene is taken out of its initial spot, leaving a space there. Already present genes are then moved to create space to accommodate the inserted gene in a separate randomly chosen location on the chromosome. The inserting gene must not contravene any problem-focused restrictions or guidelines when employing the insertion mutation. In order to preserve significant and viable solutions, an updated position must be true and practicable in the problem domain [57]. Bit flip mutation adds randomization to GA by switching the positions of GA. This randomization aids the procedure's exploration of various areas within the exploration area that can yield more advantageous solutions. It enables an expanded investigation outside the current population. It is essential for preserving genetic variation in populations. Providing arbitrary modifications that may bypass local optimum regions and encouraging the investigation of other gene arrangements, it aids in preventing preterm convergence. One gene or chromosomal piece is picked at random. The numerical representation of the chosen gene has been reversed or reversed. The reversed gene is substituted for the initial gene located on the chromosome to produce the mutant individual [57]. Last one discussed here is gaussian mutation, GA supports both explorations as well as utilization through this mutation. The exploration component is accomplished by applying arbitrary modifications to the inputs or genes, thereby helping the procedure search a wider area of the proposed solution domain. By gradually bringing solutions closer to ideal or nearly optimal outcomes, the exploitation element is accomplished. The standard deviation component of the Gaussian distribution regulates the size of the variations in this mutation. Greater variations are produced by bigger standard deviations [57], allowing for deeper study. Lower variations are caused by lower standard deviations, making finer changes and the use of the current solutions possible.

A. WORKING OF GENETIC ALGORITHM WITH OFFSPRING REFINEMENT (GAOR)

The proposed GA is responsible for the augmentation of offspring refinement for enhancement in GA. After crossover and mutation operation, there is still scope for improvement in offspring attained. The offspring refinement method proposed below repeatedly improves results by first looking in the nearby area and then migrating towards more promising

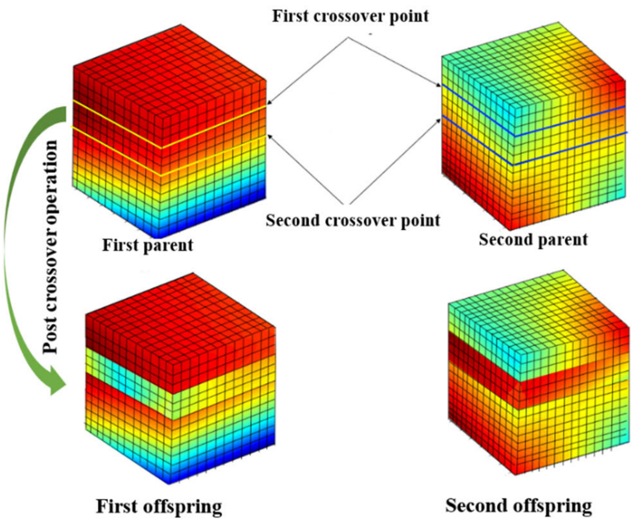


FIGURE 5. Two-point crossover mechanism in sub-chromosome SC-PD.

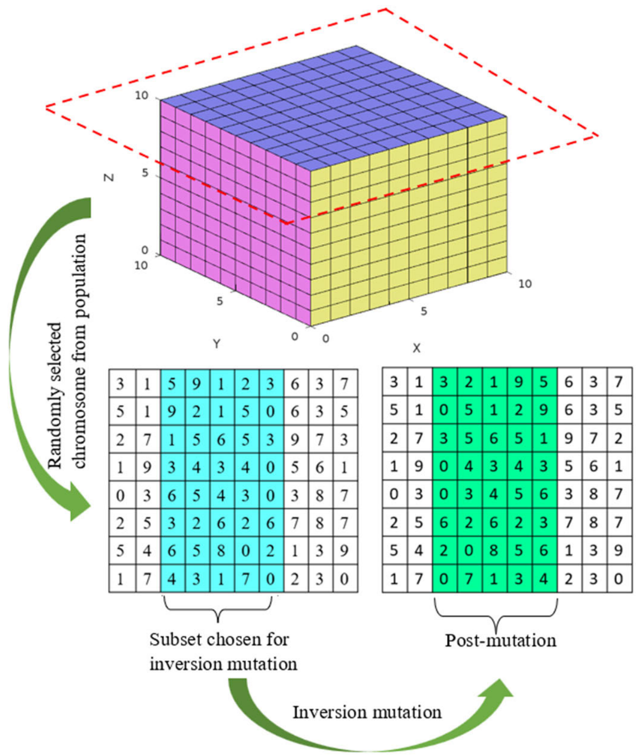


FIGURE 6. Inversion mutation functioning.

areas of the solution space. The proposed technique can effectively locate locally optimum or optimal alternatives by focusing their exploration on a specific solution. The augmentation of this technique in GA can be visualized by the procedure mentioned in the following steps:

- Step 1: Initialize the population as shown in Algorithm 1 and opt for the best population size parameter using the Taguchi experiment
- Step 2: Select a parent based on the most appropriate technique from all five techniques mentioned above. Technique selection is made based on the Taguchi experiment.
- Step 3: Avail the fitness function generated from game theory approach stated in portion dealing with fitness function under section V.
- Step 4: Post-parent selection crossover is performed and the type of crossover is chosen from the five different crossovers described in above text using Taguchi experiment.
- Step 5: After crossover, advancement of the population is necessary and for that, mutation is performed.
- Step 6: Offspring refinement is applied in order to improve the quality of offspring attained after mutation. The detailed application of this technique in GA is shown in Algorithm 2.
- Step 7: The offspring refinement terminates after witnessing any one of the two conditions firstly if there is no improvement in the population, and secondly, if a predefined number of generations has been reached.
- Step 8: Evaluate population.
- Step 9: Print the optimal result.

B. COMPUTATIONAL COMPLEXITY OF PROPOSED GAOR ALGORITHM

The assessment of the computational complexity of GAOR is a multifaceted and intricate subject like GA. Unlike deterministic algorithms, where one can offer a clear and exact analysis of computational complexity, GAOR presents a greater challenge in this regard due to their stochastic and heuristic nature, involving the exploration of a population of potential solutions. There is no general analysis that can apply to all GAs. Nonetheless, rough approximation of the computational complexity for the GAOR can be offered. The complexity of GAOR is influenced by several variables, such as the population size (X1), chromosome length (L), and the number of generations (G). An approximate assessment of both time and space complexity using the big O notation is provided, the time complexity of GAOR is O (G × (X1×L + T_OR + L)). Here, T_OR is time complexity of the offspring refinement step post mutation which is an amplification of the local search algorithm and its time complexity is O(R×N). Where, R is the run count for offspring refinement and N size of neighborhood explored. Similar approximate assessment of space complexity provides O(X1×L+S_OR) and S_OR is space complexity of offspring refinement and it is constant like LS algorithm as it stores only current solution.

VI. VERIFICATION OF PROPOSED GAOR ON CEC 2020 MULTI-OBJECTIVE BENCHMARK FUNCTIONS

The optimization performance of the proposed GAOR algorithm is evaluated using CEC 2020 [58], that comprises of twenty-four multimodal multi-objective (MMO) benchmark functions. The diverse methodical and standardized

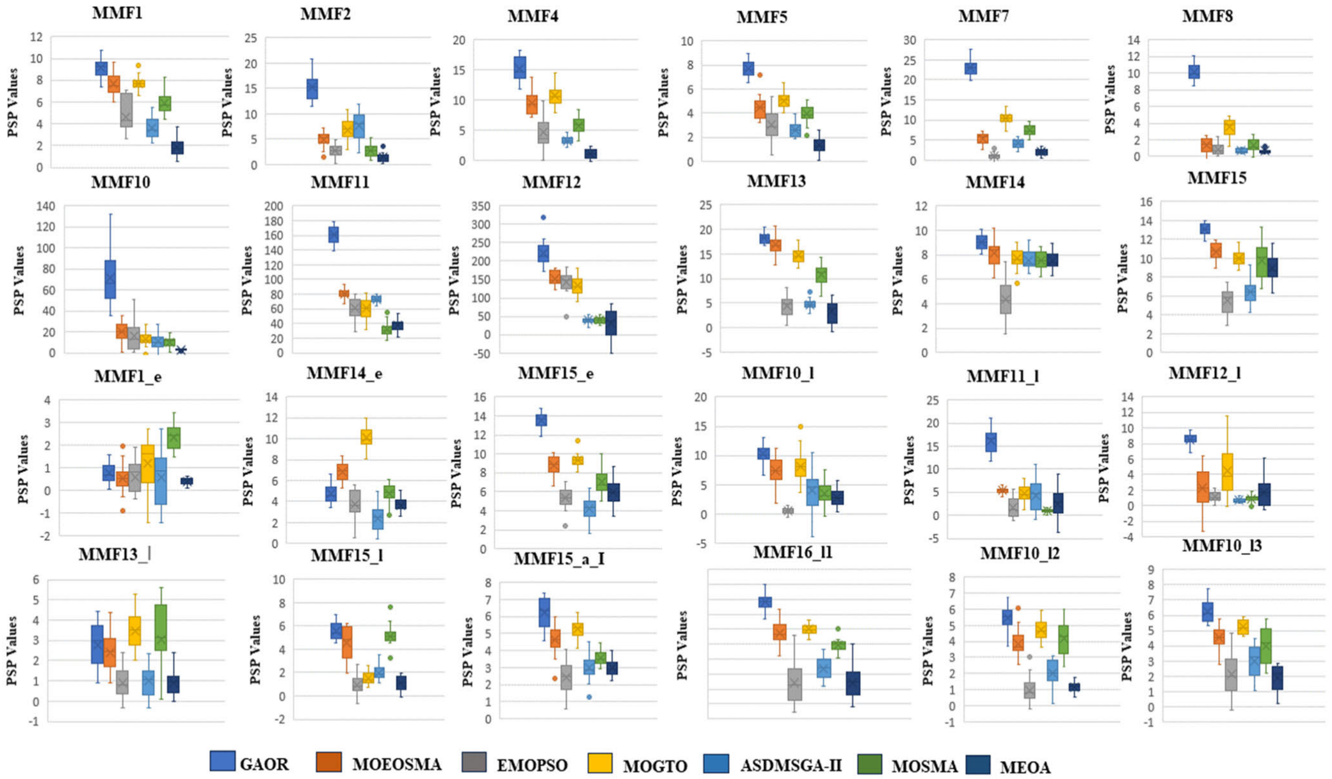


FIGURE 7. Box plot for PSP values of GAOR and other competitor MOO algorithms on CEC 2020 functions.

functions under CEC 2020 show several local or global Pareto optima, and these functions can have different forms for PF and PS. The form of the PS might be linear or non-linear, whereas the shape of the PF can be either convex or concave. The efficacy of GAOR is assessed using three performance indicators inverted generational distance in decision space (IGDX), Pareto set proximity (PSP), hyper volume (HV). The IGDX parameter calculates the mean difference between the solutions produced by the algorithm and the reference or actual solutions by utilizing the decision space [59]. It is defined as the mean Euclidean distance amidst attained PS (A) and true PS (T*). The mathematical formula for IGDX is provided in equation (15). Smaller value of IGDX is favorable as it signifies high convergence and diversity.

$$\mathrm{IGDX}\left(A,T^{*}\right)=\frac{\sum_{t\in T^{*}} dist(t,A)}{\mid T^{*}\mid} \tag{15}$$

The other vital performance indicator is PSP, it evaluates the similarity between the algorithm generated solutions and reference solutions [59]. Thus, high PSP value aligns with better algorithm. PSP evaluation as shown in equation (18) requires two vital metrices IGDX and cover rate (CR). CR is the ratio by which A and T^* overlaps. To calculate CR, minimum (m_d^{min}) and maximum (m_d^{max}) value for $d-th$ variable for A and minimum (M_d^{min}) and maximum (M_d^{max}) value for $d-th$ variable for T^* should be calculated beforehand as shown in equation (16). The formula to calculate CR is presented under equation (17).

$$Ov_d=\left\{\begin{array}{ll}0 & M_d^{max}=M_d^{min}\\ 1 & m_d^{min}\geq M_d^{max}\ ||\ m_d^{max}\leq M_d^{min}\\ \left(\frac{\min\left(m_d^{max},M_d^{max}\right)-\max\left(m_d^{min},M_d^{min}\right)}{M_d^{max}-M_d^{min}}\right) & \text{otherwise}\end{array}\right\} \tag{16}$$

$$\mathrm{CR}=\left(\prod\nolimits_{d=1}^{n} Ov_d\right)^{\frac{1}{2n}} \tag{17}$$

Here, n stands for the decision spaces dimension.

$$\mathrm{PSP}=\frac{\mathrm{CR}}{\mathrm{IGDX}} \tag{18}$$

HV, the third performance indicator gauges the volume of the objective space controlled by the generated solutions and the restriction to create this volume is provide by a point called as reference points $Ref=(Ref_1,\ldots,Ref_u)^T$ which is overpowered by all solution from PF. HV is calculated with Lebesgue metric as shown in equation (19). The higher the HV the better algorithm is considered [60].

$$\mathrm{HV}\left(A\right)=L\left(\bigcup\nolimits_{a\in A}\left[f_1\left(a\right),Ref_1\right]\times\ldots\left[f_u\left(a\right),Ref_u\right]\right) \tag{19}$$

The proposed GAOR is verified on twenty-four CEC 2020 functions and the corresponding three performance indicator matrices are calculated as shown in Table (3)-(5) using equations (15)-(18). In order to assess the performance

Algorithm 2 Algorithm for Offspring Refinement

Input: Post mutation
$P = \{P_1 UP_2\} : P_1 = \{x_{111}, \ldots, x_{ijk}\}$,
$P_2 = \{x_{1111}, \ldots, x_{jmk'l}\}$, and *Max Run count*
Output: Post refinement
$\widetilde{P} = \{\widetilde{P_1} U \widetilde{P_2}\} \widetilde{P_1} = \{x_{111}, \ldots, x_{ijk}\}$,
$\widetilde{P_2} = \{x_{1111}, \ldots, x_{jmk'l}\}$

Run Count begins at 0
Optimum Obj value is attained from the *fitness function*
Set $\widetilde{P} = P$
Initialize *Run Count* $= 0$
Set *Optimum Obj* = *fitness function*(*P*)
while *Run Count* $\leq$ *Max Run count, do the following*
  Generate a random index *i using RandomNumber () modulo(a+1)*
  Generate a random index j_1*using RandomNumber () modulo* (b_1+*1*)
  Generate a random index j_2*using RandomNumber () modulo* (b_2+*1*)
  Generate a random index *k using RandomNumber () modulo(c+1)*
  Generate a random index m_1*using RandomNumber () modulo* (d_1+*1*)
  Generate a random index m_2*using RandomNumber () modulo* (d_2+*1*)
  Generate a random index k'*using RandomNumber () modulo(f+1)*
  Generate a random index *l using RandomNumber () modulo(e+1)*
  Create a temporary copy of *P* called *Interim P*
  Swap the values of $x_{ij_1k}^{interim}$ with $x_{ij_2k}^{interim}$, and $x_{jm_1k'l}^{interim}$ with $x_{jm_2kn'l}^{interim}$ where $x_{ijk}^{interim}$ and $x_{jmk'l}^{interim}$ belong to *Interim P*
  If *fitness function (Interim P)* < *Optimum Obj,* then:
  Set $\widetilde{P}$ = *Interim P*

Increment *RunCount* by 1
Output $\widetilde{P}$ as the result

of the proposed GAOR in relation to other competitors, we conduct a comparative analysis by pitting GAOR against six robust MOO algorithms, which encompass MOEOSMA [61], EMOPSO [62], MOGTO [24], ASDMSGA-II [63], MOSMA [23], and MEOA [64].

The parameter settings listed in Table 2 is used in the testing process for every algorithm. The population dimensions, the number of fitness function evaluations, and the number of independent runs for every function was kept at constant numbers to guarantee an equitable comparison. The additional specifications were followed as suggested by the original research publications for each of them.

TABLE 2. Parameter setting of the proposed algorithm and other competitor algorithms compared.

Algorithms	Parameters
GAOR	Population size $(X1) = 125$ Crossover probability $(X2) = 0.9$ Mutation probability $(X3) = 0.13$ Parent selection method (X4) =The truncation selection Crossover type (X5) =Two-point
MEOA	Population size $(X1) = 125$
	Crossover probability $(X2) = 0.2$
	Mutation probability $(X3) = 0.4$
MOSMA	Population size $(X1) = 125$
	Constant $(z) = 0.03$
ASDNSGA-II	Population size $(X1) = 125$
	Crossover probability $(X2) = 0.9$
	Mutation probability $(X3) = 0.01$
MOGTO	Population size $(X1) = 125$
	Generation method parameter (p) =0.03
	Intensification phase parameter (w) =0.8
	Optimization state parameter (β) = 3
MOEOSMA	Hybrid parameter $(z) = 0.6$
	Generation probability $(Gp) = 0.5$
EMOPSO	Population size $(X1) = 125$ Learning parameter C1 and $C2 = 2.05$ Number of independent runs = 30

A. COMPARISON ANALYSIS BETWEEN PROPOSED GAOR AND COMPETING MOO ALGORITHMS

Various matrices including PSP, IGDX, and HV are used in this section to compare the efficiency of GAOR over other algorithms. The PSP, IGDX, and HV value for GAOR and other six MOO algorithms to be compared are provided in Table 3, Table 4, and Table 5 respectively. A specific rank is provided to each algorithm under all three parameters using Friedman test. The Friedman test is a nonparametric technique that regulates the family-wise inaccuracy and assesses the importance of variations across several methods by calculation Friedman mean rank (FMR) [62]. To study the data distribution the boxplot for all seven algorithms is plotted as shown in Figure 7. Moreover, the statistical analysis is clarified and the significance of the results is confirmed by using the Wilcoxon rank-sum test. Given the stochastic nature of MAs and their intrinsic randomness, the Wilcoxon test is used to verify that the observed performance is not random. Table 6 presents the results of the Wilcoxon test for each of the competing algorithms for PSP IGDX, and HV. The test's significance threshold is set at 5%, and all p-values, including those obtained from the PSP, IGDX, and HV metrics in the Wilcoxon validation, must be ≤ 0.05 (at a five percent level of significance). Wilcoxon test and Friedman tests are performed using IBM SPSSS software. The summary of comparison analysis of all seven algorithms is as follows:

TABLE 3. The PSP values attained by all comparison algorithms.

Functions	GAOR	MOEOSMA	EMOPSO	MOGTO	ASDNSGA-II	MOSMA	MEOA
MMF1	9.13+0.81	7.67+0.95	4.61+1.94	7.72+0.61	3.65+0.97	5.90+0.98	1.81+0.84
MMF2	15.33+6.88	4.92+1.40	2.76+1.13	6.84+2.01	7.66+2.67	2.77+1.15	1.39+0.82
MMF4	15.13+1.94	9.40+1.70	4.56+2.62	10.66+1.44	3.27+0.62	5.77+1.22	1.07+0.76
MMF5	7.66+0.67	4.48+0.93	3.02+1.23	5.04+0.60	2.59+0.56	3.92+0.68	1.33+0.57
MMF7	23.03+1.81	5.43+1.27	1.00+0.78	10.46+1.42	4.16+1.06	7.37+1.30	2.00+0.86
MMF8	10.11+0.93	1.30+0.80	0.72+0.77	3.53+1.00	0.69+0.25	1.31+0.68	0.66+0.24
MMF10	71.13+42.45	19.98+9.34	15.56+20.68	13.26+6.53	10.79+6.93	10.31+4.59	2.90+0.54
MMF11	160.53+11.05	80.58+6.03	60.46+13.28	73.26+4.22	32.29+8.66	37.93+8.50	36.26+12.31
MMF12	221.53+31.95	152.18+18.35	143.46+28.28	134.36+24.97	16.49+28.13	39.43+8.29	32.56+35.01
MMF13	18.23+1.02	16.88+1.71	4.40+2.19	14.66+1.59	4.71+0.93	10.73+1.93	3.27+2.24
MMF14	9.06+0.56	8.11+0.94	4.36+1.50	7.67+0.80	7.55+0.75	7.52+0.67	7.69+0.73
MMF15	13.03+0.57	10.68+0.89	5.49+1.33	10.01+0.75	6.42+1.22	9.71+1.75	8.96+1.31
MMF1_e	0.76+0.43	0.56+0.66	0.60+0.67	1.22+1.03	0.57+0.18	2.35+0.54	0.41+0.15
MMF14_e	4.77+0.87	6.85+0.84	3.74+1.31	10.13+0.98	2.41+1.13	4.72+0.90	3.66+0.59
MMF15_a	13.53+0.72	8.81+0.94	5.35+1.08	9.36+0.67	4.18+1.11	7.01+1.26	5.91+1.27
MMF10_I	10.24+1.50	7.45+2.38	0.58+0.60	8.12+2.64	4.15+3.56	3.51+1.82	2.72+1.47
MMF11_I	16.23+2.49	5.30+0.64	1.72+2.15	4.77+1.89	4.25+3.42	0.92+0.40	2.38+2.92
MMF12_I	8.47+0.72	2.21+2.47	1.15+0.65	4.47+2.89	0.67+0.27	0.89+0.44	1.72+1.80
MMF13_I	2.77+1.03	2.37+0.85	0.89+0.70	3.44+0.90	1.02+0.71	3.05+2.04	0.90+0.56
MMF15_I	5.61+0.76	4.51+1.41	0.90+0.77	1.51+0.51	1.99+0.63	5.13+0.90	1.10+0.58
MMF15_a_I	6.23+0.84	4.63+0.82	2.42+0.99	5.30+0.51	3.01+0.73	3.54+0.42	2.97+0.42
MMF16_l1	7.85+0.51	5.73+0.80	2.43+1.45	6.00+0.38	3.38+0.74	4.94+1.04	2.43+1.11
MMF16_l2	5.44+0.76	3.85+0.84	0.97+0.75	4.71+0.63	2.03+0.77	4.20+0.98	1.16+0.27
MMF16_l3	6.27+0.71	4.52+0.65	2.16+1.25	5.26+0.46	3.00+1.00	3.99+1.10	1.94+0.78
FMR	6.75	5.00	2.31	5.50	2.63	3.88	1.94
Rank	1	3	6	2	5	4	7

- The Statistical outcomes of the PSP values in terms of mean and standard deviation (SD) on 25 runs of every algorithm are reported under Table 3. Availing the Friedman test, FMR is calculated for all seven algorithms and it is found that the overall performance order for the tested algorithms GAOR, MOEOSMA, EMOPSO, MOGTO, ASDMSGA-II, MOSMA, and MEOA based on FMR is 1, 3, 6, 2, 5, 4, and 7 respectively. However, there are some instances where GAOR is outperformed by other algorithms say for MMF1_e and MMF13_I, MOGTO and MOSMA outperforms GAOR. For function MMF14_e MOESMA outperforms GAOR.
- The box plots of developed in Figure 7 shows that GAOR have the highest and tightly packed PSP values for most CEC 2020 functions except for MMF1_e, MMF13_I, and MMF14_e functions.
- Table 4 holding the IGDX metric statistical results in context of mean and SD for 25 runs for each algorithm. The rank for GAOR, MOEOSMA, EMOPSO, MOGTO, ASDMSGA-II, MOSMA, and MEOA for IGDX is 1, 2, 5, 3, 7, 4, and 6. Whereas, in some cases GAOR is outperformed by other algorithms say for CEC 2020 functions MMF1_e, MMF14_e algorithms MOEOSMA, MOGTO, MOSMA yields less IGDX value as compared to GAOR. For MMF13_I IGDX value of MOEOSMA is less than GAOR.
- The statistical values of HV in context of mean and SD are accommodated under Table 5. For HV, the higher the FMR of algorithm better the algorithm.
  The rank of GAOR, MOEOSMA, EMOPSO, MOGTO, ASDMSGA-II, MOSMA, and MEOA based on FMR is 1, 3, 5, 2, 6, 4, and 7. For functions MMF4 and MMF7 GAOR is outperformed by MOEOSMA, MOGTO, and MOSMA. For MMF8 MOGTO gives higher value of HV as compared to GAOR. Under MMF12 MOGTO and MEOA yields higher HV values in contrast to GAOR. EMOPSO and MOSMA perform better for MMF14_e in terms of HV values.
- The Wilcoxon test has been conducted on all three algorithm matrices to demonstrate that the performance of GAOR is not random. The Wilcoxon rank-sum test, a nonparametric statistical test, is utilized to compare the outcomes achieved by each pair of algorithms. This test is rooted in two hypotheses: the null hypothesis posits that there is no disparity in the ranks of results obtained by a pair of algorithms, while the alternative hypothesis suggests that there exists a divergence in the ranks of these results [65], [66]. In this case, the Wilcoxon

TABLE 4. The IGDX values attained by all comparison algorithms.

Functions	GAOR	MOEOSMA	EMOPSO	MOGTO	ASDNSGA-II	MOSMA	MEOA
MMF1	0.173+0.024	0.212+0.026	0.330+0.086	0.241+0.032	0.623+0.130	0.318+0.047	0.410+0.079
MMF2	0.127+0.041	0.223+0.057	0.504+0.066	0.277+0.045	0.580+0.156	0.543+0.105	0.270+0.059
MMF4	0.128+0.027	0.175+0.030	0.356+0.130	0.216+0.042	0.545+0.111	0.326+0.058	0.428+0.059
MMF5	0.199+0.025	0.288+0.035	0.459+0.091	0.336+0.053	0.979+0.499	0.427+0.062	0.523+0.077
MMF7	0.104+0.020	0.175+0.027	0.419+0.050	0.232+0.033	0.435+0.089	0.278+0.045	0.316+0.069
MMF8	0.163+0.023	0.406+0.122	2.180+0.790	0.996+0.339	2.310+0.680	1.430+0.430	2.760+0.594
MMF10	0.122+0.115	0.181+0.082	0.257+0.159	0.178+0.075	0.513+0.088	0.249+0.066	0.247+0.078
MMF11	0.066+0.017	0.094+0.019	0.107+0.023	0.122+0.021	0.180+0.039	0.158+0.030	0.153+0.029
MMF12	0.065+0.018	0.088+0.019	0.097+0.020	0.117+0.021	0.245+0.150	0.157+0.031	0.303+0.115
MMF13	0.116+0.020	0.149+0.026	0.234+0.055	0.168+0.026	0.366+0.121	0.231+0.040	0.841+0.132
MMF14	0.177+0.021	0.217+0.030	0.336+0.074	0.235+0.033	0.287+0.038	0.276+0.031	0.263+0.034
MMF15	0.140+0.019	0.184+0.024	0.256+0.036	0.205+0.026	0.267+0.044	0.242+0.039	0.274+0.044
MMF1_e	2.600+0.915	1.120+0.511	3.340+1.359	2.390+1.040	4.060+0.968	0.705+0.105	3.400+0.550
MMF14_e	0.300+0.053	0.182+0.026	0.360+0.052	0.259+0.033	0.431+0.059	0.378+0.058	0.503+0.122
MMF15_a	0.137+0.020	0.191+0.024	0.269+0.031	0.225+0.029	0.321+0.048	0.288+0.046	0.339+0.047
MMF10_I	0.162+0.029	0.200+0.046	0.299+0.021	0.238+0.044	0.368+0.054	0.323+0.044	0.432+0.239
MMF11_I	0.141+0.053	0.260+0.053	0.329+0.064	0.318+0.070	0.425+0.078	0.388+0.027	0.368+0.082
MMF12_I	0.186+0.025	0.269+0.065	0.335+0.020	0.334+0.056	0.409+0.045	0.379+0.024	0.491+0.119
MMF13_I	0.365+0.061	0.321+0.037	0.466+0.039	0.381+0.033	0.548+0.052	0.389+0.071	0.500+0.042
MMF15_I	0.258+0.039	0.386+0.024	0.514+0.043	0.331+0.053	0.472+0.035	0.354+0.052	0.456+0.041
MMF15_a_I	0.234+0.034	0.281+0.033	0.414+0.041	0.326+0.044	0.452+0.068	0.409+0.035	0.408+0.044
MMF16_l1	0.197+0.022	0.258+0.025	0.400+0.069	0.289+0.036	0.434+0.065	0.345+0.038	0.406+0.055
MMF16_l2	0.265+0.038	0.311+0.043	0.549+0.040	0.374+0.049	0.516+0.068	0.392+0.055	0.495+0.055
MMF16_l3	0.234+0.029	0.283+0.029	0.431+0.062	0.331+0.035	0.459+0.054	0.380+0.050	0.420+0.059
FMR	1.24	2.04	5.04	3.00	6.56	4.40	5.72
Rank	1	2	5	3	7	4	6

rank-sum test employs a 5% significance level with all p-values ≤ 0.05 (at a five percent level of significance) for all outcomes, including the analytical results derived from the PSP, IGDX, and HV metrics. Nevertheless, the results of the Wilcoxon assessment for each paired algorithm in the comparison test for problem sets (PSs) are presented in Table 6, and it is evident from the data of Table 6 that proposed GAOR is not subject to random fluctuations.

VII. NUMERICAL EXPERIMENT WITH REAL LIFE CASE STUDY

Here, data from real-world situations are used to illustrate the research. In mountainous areas with difficult topography, handling solid waste has not received enough attention in past decades. Numerous Indian cities use a linear strategy to garbage management, which entails collecting trash, transit, and dumping in landfills. Bizarrely, 80–90% of the garbage is carelessly deposited at landfills in these locations, exposing a sizable amount of created waste that is not picked up by municipal authorities. Due to the complex environment, topography, and temperature, LFM ancient dumpsites in mountainous areas are fraught with difficulties [67]. Legacy waste management calls for meticulous care and competence, from assessment through disposal. Due to several operational and technological challenges, the management and elimination of residual waste components in such places are expected to be costly. To tackle this kind of situation in hilly regions, the research work has considered a case study from the state of Uttarakhand in India.

In the northern, mountainous area of India, Uttarakhand, there is a sizable inflow of tourists. The Municipal Solid Waste (Management and Handling) Rules were enacted by the governing body in 2000 to protect the area's scenic splendor. The state is jointly responsible for carrying out the 2016 solid waste management (SWM) regulations, which are monitored by ninety-one urban local governments and nine cantonment boards. As per the data from the official website of the Uttarakhand pollution control board [68], the major landfill sites in the state are situated in Roorkee, Pithoragarh, Sitarganj, and Kashipur. However, as per the data from SWM annual report for the year 2020-21 [69], the waste processing plant lies in Haridwar and Dehradun. Consumers and prospective customers of the new value-added product generated post-processing from the landfill waste that includes scrap combustive material refuse-derived fuel, recycled aggregate concrete, and concrete are in Rudrapur, Shivalik Nagar, and Kotdwar [70]. The data for the numerical

TABLE 5. The HV values attained by all comparison algorithms.

Functions	GAOR	MOEOSMA	EMOPSO	MOGTO	ASDNSGA-II	MOSMA	MEOA
MMF1	0.96+0.02	0.93+0.02	0.90+0.02	0.91+0.17	0.91+0.03	0.94+0.05	0.80+0.18
MMF2	0.84+0.03	0.79+0.06	0.82+0.04	0.82+0.20	0.67+0.13	0.66+0.07	0.84+0.06
MMF4	0.57+0.02	0.59+0.02	0.57+0.02	0.64+0.12	0.58+0.03	0.64+0.04	0.28+0.77
MMF5	0.91+0.01	0.92+0.02	0.90+0.02	0.88+0.18	0.92+0.02	0.90+0.10	0.92+0.05
MMF7	0.91+0.01	0.92+0.02	0.90+0.02	0.94+0.14	0.90+0.02	0.94+0.06	0.82+0.13
MMF8	0.46+0.01	0.35+0.14	0.42+0.04	0.50+0.13	0.43+0.04	0.36+0.19	2.27+0.15
MMF10	12.64+0.38	12.27+0.21	12.05+0.27	11.72+0.27	12.27+0.45	10.1+0.85	11.69+0.17
MMF11	14.54+0.02	14.47+0.05	14.45+0.04	14.12+0.32	14.47+0.04	13.45+0.67	13.99+0.23
MMF12	1.61+0.01	1.62+0.04	1.59+0.03	0.75+0.41	1.60+0.07	1.43+0.21	2.56+0.85
MMF13	18.44+0.04	18.37+0.05	18.15+0.09	17.82+0.33	18.27+0.06	16.75+0.78	16.89+180.02
MMF14	3.13+0.15	2.80+0.31	2.53+0.31	3.19+0.44	2.48+0.25	3.21+0.42	3.09+0.28
MMF15	4.30+0.19	4.05+0.43	3.71+0.38	4.30+0.35	3.60+0.31	4.21+0.35	3.66+0.86
MMF1_e	0.87+0.06	0.87+0.10	0.84+0.06	1.00+32.52	0.73+0.38	0.69+3.53	0.87+0.08
MMF14_e	2.92+0.30	2.63+0.23	3.24+0.24	2.90+0.45	2.47+0.65	3.17+0.42	2.41+0.40
MMF15_a	4.64+0.38	3.88+0.28	3.73+3.70	4.31+0.38	3.86+0.39	4.22+0.35	3.16+0.49
MMF10_I	17.84+0.04	11.67+0.19	11.75+0.17	11.42+0.25	11.47+0.06	10.35+0.78	16.09+0.32
MMF11_I	74.04+1.01	14.27+0.09	14.15+0.13	14.52+0.16	14.37+0.08	11.75+1.76	13.49+0.34
MMF12_I	2.36+0.02	1.62+0.02	1.55+0.06	1.20+0.33	1.62+0.05	1.32+0.20	1.66+0.62
MMF13_I	17.54+0.30	18.37+0.05	18.95+0.02	18.42+0.29	18.27+0.05	17.05+0.98	18.19+0.14
MMF15_I	4.17+0.17	4.08+0.61	3.82+0.38	3.90+0.43	2.81+0.32	4.08+0.34	3.97+0.96
MMF15_a_I	4.70+1.01	4.07+0.35	3.95+0.21	4.51+0.51	3.33+0.43	4.45+0.40	3.36+0.41
MMF16_l1	4.60+0.61	4.16+0.32	3.81+0.47	4.33+0.26	3.53+0.54	4.32+0.25	3.39+0.57
MMF16_l2	4.45+0.47	4.07+0.58	4.13+0.38	4.32+0.23	2.97+0.36	4.22+0.35	3.62+0.66
MMF16_l3	4.26+0.22	4.08+0.43	3.64+0.21	4.29+0.21	3.87+0.27	4.23+0.31	3.23+0.79
FMR	5.48	4.3	3.46	4.58	3.34	3.56	3.26
Rank	1	3	5	2	6	4	7

TABLE 6. The Wilcoxon values attained between GAOR other comparison algorithms.

Test metric	GAOR vs MOEOSMA	GAOR vs EMOPSO	GAOR vs MOGTO	GAOR vs ASDNSGA-II	GAOR vs MOSMA	GAOR vs MEOA
PSP	4.57E-05	1.229E-05	1.40E-04	1.229E-05	3.624E-05	1.229E-05
IGDX	5.11E-03	1.82E-05	3.55E-04	1.82E-05	3.18E-04	1.82E-05
HV	1.91E-03	1.63E-03	2.53E-02	3.50E-04	7.45E-04	8.54E-03

experiment was compiled from numerous databases since one stakeholder did not have access to all the information requisite. For the location of dumping/ landfill sites, processing sites, demand points, and waste holding capacity, [68] and [69] are considered. The costs are considered based on the data attained from Annexure 17.1 of Chapter 17 of the Central Public Health and Environmental Engineering Organization (CPHEEO) and Nagar Nigam reports [71]. Inputs regarding carbon emission were derived from the following resources [72] and [73], as these work gives estimation of emission in landfills mining. All the data considered in the model is taken as fuzzy to accommodate discrepancies caused by geographical location and time. The inputs for model parameters are provided in Table 7, 8, and 9.

A. RESULTS ATTAINED USING GAOR ALGORITHM

The MOMLSTM present in subsection E of section III is implemented in a case study from Uttarakhand, as stated earlier in this section. For capturing uncertainty, the model is developed, availing fuzzy parameters. The first step toward a solution is to convert the fuzzy values into crisp values using the methodology shown in subsection B of section IV. Post attaining a crisp model, the multi-objective model is solved using the non-deterministic approach proposed GAOR. However, this technique requires parameter tuning of the algorithm. GAOR's accomplishment and efficacy are greatly influenced by parameter configuration. A GAOR's converging pace, solution excellence, exploration-exploitation equilibrium and ultimate optimization ability may all be greatly

TABLE 7. Inputs for parameters of MOMLSTM in PFN format in case study.

	$\widetilde{TCT}_{jmk'}$			
j	m	$k'=1$	$k'=2$	$k'=3$
1	1	(7.9,8.5,9.6,11.7,12.5,0.6)	(7.9,8.9,9.6,11.7,12.5,0.6)	(8,8.9,10.9,11.7,12.5,0.7)
	2	(8,8.9,10.9,11.7,12.5,0.8)	(7.5,8.2,9.5,10.8,12.7,0.8)	(7.5,8.2,9.5,9.9,11.9,0.8)
	3	(8,8.9,10.9,11.7,12.5,0.7)	(7.5,8.2,9.6,10.8,11.9,0.8)	(8.4,9.8,11,11.9,13.5,0.5)
2	1	(7.5,7.8,8.1,8.2,10.2,0.7)	(7.5,8.2,9.6,10.8,11.5,0.5)	(7.5,7.8,8.1,11.5,0.6)
	2	(8,8.9,10.7,11.7,12.1,0.7)	(8,9.5,10.4,13.2,14.2,0.9)	(9.5,10.4,13.2,14.2,0.9)
	3	(7.5,8.2,9.5,10.8,12.7,0.8)	(8,9.4,10,13.4,13.8,0.7)	(7.9,9.4,11.1,11.7,12.5,0.7)
	$\widetilde{TTT}_{jmk'}$			
j	m	$k'=1$	$k'=2$	$k'=3$
1	1	(11.4,13.5,15.6,17.7,22.4,0.8)	(12.4,14.5,16.8,18.9,22.9,0.8)	(12.4,14.8,18.8,20.1,25.6)
	2	(13.2,14.9,16.8,18.9,22.9,0.8)	(13.2,14.9,16.9,18.9,22.5,0.8)	(12.9,16.3,18.8,22.5,25.6,0.8)
	3	(14.1,16.3,18.8,22.6,25.5,0.8)	(12.4,14.8,18.8,20.1,25.6,0.8)	(13.2,14.9,16.8,18.9,22.9,0.8)
2	1	(11.5,15.2,15.6,17.7,26.3,0.8)	(12.3,14.7,16.9,18.9,23.2,0.8)	(12.4,14.8,18.8,20.1,26.3,0.8)
	2	(12.4,14.8,18.8,20.1,27.7,0.8)	(13.2,15.5,19.1,22.5,25.6,0.8)	(11.5,15.2,16.2,17.8,25.9,0.8)
	3	(14.1,16.3,17.3,22.3,25.5,0.8)	(11.9,14.9,19.1,20.1,26.3,0.8)	(12.8,15.5,19.1,22.5,25.6,0.8)
	$\widetilde{CTT}_{jmk'}$			
j	m	$k'=1$	$k'=2$	$k'=3$
1	1	(16.5,19.5,21.6,24.5,35.5,0.4)	(16.5,19.5,21.6,26.5,38.5,0.5)	(16.5,19.5,21.6,24.5,31.5,0.6)
	2	(12.5,19.5,21.6,24.5,31.5,0.6)	(10.9,19.5,21.6,23.5,30.5,0.6)	(12.5,19.5,21.6,24.5,31.5,0.6)
	3	(19.5,20.5,22.5,26.5,38.5,0.5)	(16.5,19.5,21.6,24.5,31.5,0.6)	(19.5,20.5,22.5,26.5,38.5,0.5)
2	1	(19.5,20.5,22.5,29.6,40.5,0.5)	(19.5,20.5,22.5,33.6,39.1,0.8)	(16.5,19.5,21.6,24.5,35.5,0.5)
	2	(19.5,20.5,22.5,3.6,39.1,0.8)	(16.5,19.5,21.6,24.5,35.5,0.5)	(16.5,19.5,21.6,24.5,31.5,0.6)
	3	(16.5,19.5,21.6,24.5,31.5,0.6)	(16.5,19.5,21.6,24.5,35.5,0.8)	(12.5,19.5,21.6,24.5,31.5,0.6)
			$\tilde{I}_{jl}$	
j		$l=1$	$l=2$	$l=3$
1		(5.8,6.3,7.8,8.1,8.9,0.6)	(5.4,6.3,7.6,8.1,8.9,0.6)	(5.4,6.3,7.2,8.1,8.5,0.6)
2		(5.6,6.4,7.2,8.1,10.2,0.8)	(2.5,4.8,7.5,8.3,11.8,0.9)	(5.5,6.5,7.3,8.1,9.5,0.6)
			$\widetilde{CI}_{jl}$	
j		$l=1$	$l=2$	$l=3$
1		(4,6.2,7.2,8.2,9.2,0.9)	(5.1,6.2,7.2,8.2,9.2,0.9)	(2.8,4.2,5.9,6.8,8.1,0.6)
2		(3.3,5.4,6.8,7.2,8.9,0.9)	(5.8,6.3,7.8,8.1,8.9,0.6)	(1.9,3.3,3.9,4.4,4.9,0.8)
			$\tilde{B}_{ml}$	
m		$l=1$	$l=2$	$l=3$
1		(568,678,788,9971106,0.6)	(111,137,145,156,218,0.5)	(185,189,211,224,298,0.8)
2		(294,323,337,367,398,0.6)	(387,410,416,423,510,0.5)	(457,467,498,521,635,0.8)
3		(185,189,211,225,310,0.6)	(214,324,337,367,398,0.5)	(387,410,416,423,537,0.8)
			$\tilde{A}_{jl}$	
j		$l=1$	$l=2$	$l=3$
1		(16789,18743,19053,22644,38599,0.6)	(19836,22873,35093,39086,481898,0.5)	(67836,68926,69349,85165,94653,0.8)
2		(59875,61086,62085,67524,75438,0.6)	(37862,38764,39086,4183,56148,0.5)	(64367,66753,71468,82468,92365,0.7)
			$\tilde{V}_{k'}$	
		$k'=1$	$k'=2$	$k'=3$
		(87354,88634,97591,98736,0.6)	(78976,79864,81037,82754,98607,0.5)	(78976,79864,81037,82754,98607,0.8)
			$\tilde{c}_k$	
		$k=1$	$k=2$	$k=3$
		(158558,178953,299753,320985346337,0.6)	(29826,33086,39864,44791,67649,0.5)	(11345,12457,13487,14965,25722,0.8)

impacted by the proper parameterization setting [74]. Thus, with the purpose of identifying the most appropriate parameter setting that yields optimal results for our problem, Taguchi experiment is used [75]. It is a method associated with statistical experimentation utilized to optimize configurations or variables in a variety of processes, including GAOR. Implementation of Taguchi in the GAOR is performed as shown in Figure 8. Various levels for the parameter setting are stated in Table 10. Values of S-T-N ratio based on methodology present in Figure 8 are given Table 11. Finally mean of S-T-N ratio for every parameter at each level is shown in Figure 9, based on the figure the best level for parameters

TABLE 8. Inputs for parameters of MOMLSTM in PFN format in case study.

		SS_{ij}			
	j	$i=1$	$i=2$	$i=3$	$i=4$
	1	(8,9.4,10,13.4,13.8,0.7)	(8.4,9.8,10.9,11.9,13.2,0.5)	(8,9.5,10.4,13.2,14.2,0.9)	(8,8.9,10.9,11.6,13.4,0.6)
	2	(8,9.5,10.4,13.2,14.2,0.9)	(8.5,9.8,10.8,11.8,12.7,0.9)	(8,8.9,10.9,11.7,12.7,0.7)	(8.4,9.8,11.1,11.9,13.5,0.5)
	j	$\widetilde{TPP}_{ij}$			
	1	(22.5.28.5.33.5.37.2.40.2.0.8)	(21.5.27.5.33.5.37.2.40.2.0.8)	(22.5.28.5.31.5.37.2.42.2.0.8)	(26.5.23.5.31.5.32.2.41.2.0.8)
	2	(24.8,30.1,33.5,39.5,49.5,0.8)	(25.8,31.1,32.5,35.5,49.5,0.8)	(26.8,32.1,34.5,38.5,49.5,0.8)	(24.8,30.1,33.5,39.5,49.5,0.8)
	j	$\widetilde{PP}_{ij}$			
	1	(8,12.7,12.9,14.1,14.6,0.7)	(9.8,11.2,13.6,14.1,17.1,0.8)	(9.2,12.7,12.9,13.9,14.9,0.6)	(8,8.9,10.9,11.7,12.5,0.8)
	2	(8.9,12.7,12.9,14.1,14.6,0.6)	(9.8,13,13.9,14.3,14.6,0.9)	(9.9,11.3,13.2,14.4,17.1,0.7)	(8.9,12.7,12.9,14.1,14.6,0.6)
		$\widetilde{TC}_{ijk}$			
k	j	$i=1$	$i=2$	$i=3$	$i=4$
1	1	(6,7,8,9,10,0.8)	(6,7,8,9,10,0.8)	(6.5,7.5,8,8.8,9.3,0.8)	(5.4,6.3,7,8.1,10.3,0.6)
	2	(5,6,7,8,9,0.9)	(4.9,6.3,7.1,7.6,9.2,0.5)	(7.5,8.2,9.5,9.8,11.6,0.8)	(7.5,8.2,9.8,11.6,0.8)
2	1	(2.5,3.4,8.1,8.3,11.5,0.6)	(6.8,8.7,9,10,11,0.9)	(7.5,7.8,8.1,8.2,10.2,0.7)	(7.1,7.9,9.2,10.4,11.4,0.8)
	2	(6.8,8.7,9,10,11,0.9)	(4.5,8.5,9.5,11.7,11.5,0.6)	(7.5,7.8,8.1,8.5,10.5,0.6)	(5.5,6.5,7.5,8.5,9.5,0.6)
3	1	(3.5,4.2,5.4,6.4,9,0.8)	(6.8,7.8,8.1,8.2,10.2,0.7)	(4.7,5,5.5,7.8,9.3,0.9)	(2.5,3.6,4.6,6.7,9.6,0.8)
	2	(7.5,8.5,9.5,11.7,12.5,0.6)	(2.5,4.8,7.5,8.3,11.5,0.9)	(5.6,6.4,7.2,8.1,10.2,0.8)	(2.4,3.7,4.6,6.7,8.1,0.8)
		$\widetilde{CC}_{ijk}$			
k	j	$i=1$	$i=2$	$i=3$	$i=4$
1	1	(2.5,3.2,3.9,5.6,6.9,0.6)	(3.5,4.2,5.4,6.4,8.5,0.8)	(2.5,3.2,3.9,4.6,5.3,0.6)	(3.5,4.2,5.4,6.9,9,0.8)
	2	(2.4,3.7,4.6,6.7,8.1,0.8)	(2.5,3.4,8,8.3,10.3,0.6)	(2.5,3.2,4,5.6,7.3,0.6)	(2.5,4,5.6,7.3,0.6)
2	1	(2,2.5,3.2,3.9,6.2,7.2,0.6)	(2.5,3.2,3.9,5.6,8.8,0.6)	(2.4,3.7,4.9,6.7,8.8,0.8)	(2.5,3.2,3.9,6.2,7.2,0.6)
	2	(2.4,3.7,4.6,6.8,8.4,0.8)	(2.4,3.7,4.9,6.7,8.8,0.8)	(2.5,3.6,4.5,7.2,9.6,0.8)	(2.5,3.4,7.9,8.4,10.1,0.6)
3	1	(3.5,4.2,5.4,6.4,9,0.8)	(5.4,6.3,7.6,8.1,8.9,0.6)	(2.5,3.6,4.6,6.7,9.6,0.8)	(2.5,3.4,7.9,8.4,9.6,0.6)
	2	(3.5,4.2,5.5,6.9,9.7,0.8)	(2.5,3.2,3.9,5.6,6.9,0.6)	(2.4,3.7,4.9,6.7,8.8,0.8)	(2.5,3.4,7.9,8.4,9.6,0.6)
		$\widetilde{TT}_{ijk}$			
k	j	$i=1$	$i=2$	$i=3$	$i=4$
1	1	(8,9.4,10,13.4,13.5,0.7)	(7.7,12.7,12.9,14.1,14.6,0.7)	(8,12.7,12.9,14.1,14.6,0.7)	(8.7,12.6,13,14.1,14.6,.7)
	2	(7.5,12.7,12.9,14.1,14.6,0.7)	(8.9,9.5,10.2,13.2,15.6,0.9)	(8,12.7,12.9,14.2,14.9,0.7)	(9.2,12.7,12.9,13.9,14.9,0.6)
2	1	(8.9,9.5,10.2,13.2,14.1,0.9)	(8.9,9.5,10.2,13.2,14.1,0.9)	(8.9,12.7,12.9,14.1,14.6,0.6)	(9.9,12.7,12.9,13.9,14.9,0.6)
	2	(7.5,12.7,12.9,14.1,18.2,0.7)	(8.9,9.5,10.2,13.2,13.7,0.9)	(8.7,12.6,12.9,14.1,14.6,0.7)	(8,12.7,12.9,14.1,0.7)
3	1	(7.5,12.7,12.9,14.1,14.6,0.7)	(8.9,9.5,10.2,13.3,14.8,0.9)	(8,12.7,12.9,14.2,14.9,0.7)	(10,11,13,16.8,18.5,0.7)
	2	(8.7,12.6,12.9,14.1,0.7)	(8.9,9.5,10.3,13.3,15.1,0.9)	(9.2,12.7,12.9,13.9,14.9,0.6)	(10.1,14.2,15.3,16.5,18.6, 0.7)
		$\widetilde{CT}_{ijk}$			
k	j	$i=1$	$i=2$	$i=3$	$i=4$
1	1	(16.5,19.5,21.6,26.5,38.5,0.5)	(16.5,19.5,21.6,24.5,31.5,0.6)	(20.5,22.5,26.5,38.5,0.5)	(19.5,20.5,22.5,33.6,43.1,0.8)
	2	(12.5,19.5,21.6,24.5,31.5,0.6)	(19.5,20.5,22.5,26.5,38.5,0.5)	(19.5,20.5,22.5,33.6,39.1,0.8)	(16.5,19.5,21.6,24.5,35.5,0.9)
2	1	(16.5,19.5,21.6,24.5,31.5,0.6)	(19.5,20.5,22.5,29.6,40.5,0.5)	(19.5,20.5,22.5,29.6,40.5,0.5)	(19.5,20.5,22.5,26.5,38.5,0.5)
	2	(16.5,19.5,21.6,24.5,35.5,0.6)	(10.9,19.5,21.6,23.5,30.5,0.6)	(19.5,20.5,22.5,33.6,43.1,0.8)	(19.5,20.5,22.5,29.6,40.6,0.5)
3	1	(12.5,19.5,21.6,24.5,31.5,0.6)	(19.5,20.5,22.5,33.6,41.5,0.5)	(19.5,20.5,22.5,29.6,40.5,0.5)	(16.5,19.5,21.6,26.5,38.5,0.5)
	2	(16.5,19.5,21.6,26.5,38.5,0.5)	(16.5,19.5,21.6,26.5,38.5,0.5)	(19.5,20.5,22.5,29.6,40.5,0.5)	(16.5,19.5,21.6,26.5,38.5,0.5)

and operators X1, X2, X3, X4, X5, and X6 is 5, 5, 4, 3, 5, and 2 respectively. The optimal solution of the MOMLSTM is attained using GAOR is mentioned in Table 12.

The validation of the solution is performed in later sections using deterministic approach of ECM in subsection B of section VI. For comparing the functioning and efficiency of GAOR the comparison from previous literature is present in sub-section C. *Note:* The orthogonal array for the experiment is considered based on the total degree of freedom. Here, the orthogonal array holds one degree of freedom for average value; and four degrees of freedom for each of the six parameters. Thus, the total degree of freedom is $1 + 6 \times 4 = 25$. The corresponding orthogonal array must contain at 25 rows. L25 array satisfies these conditions and act as appropriate orthogonal array for experiment.

B. VALIDATION OF RESULTS USING DETERMININSTIC APPROACH: EPSILON CONSTRAINT METHOD

For validating the results attained using GAOR a deterministic approach i.e., ECM is used, it is one of the most distinguished deterministic approaches used to solve MOMLSTM. In past it is adequately leveraged to solve multi-objective models as shown in literature [76] and [77]. The primary functioning of this approach revolves around the concept of optimizing any one of the objectives and setting other

TABLE 9. Inputs for parameters of MOMLSTM in PFN format in case study.

<table>
<tr><td>$\widetilde{PFS}$</td><td>$\widetilde{SED}$</td><td>$\widetilde{SBI}$</td><td>$\widetilde{CL}$</td></tr>
<tr><td>(15,17,18,19,21,0.8)</td><td>(18,20,22,24,26,0.5)</td><td>(10,11,13,14,17,0.7)</td><td>(16.5,19.5,21.6,24.5,31.5,0.6)</td></tr>
<tr><td>$\widetilde{CE}$</td><td>$\widetilde{TPF}$</td><td>$\widetilde{TED}$</td><td>$\widetilde{TSB}$</td></tr>
<tr><td>(11.5,15.2,15.6,17.8,19.8,0.8)</td><td>(22.5,28.5,33.5,38.5,46.5)</td><td>(4.9,6.3,7.8,8.1,8.5,0.6)</td><td>(2.4,3.7,4.9,6.7,8.8,0.8)</td></tr>
<tr><td>$\widetilde{TSS}_1$</td><td>$\widetilde{TSS}_2$</td><td>$\widetilde{CP}_1$</td><td>$\widetilde{CP}_2$</td></tr>
<tr><td>(22.5,28.5,33.5,37.2,40.2,0.8)</td><td>(24.8,30.1,33.5,39.5,49.5,0.8)</td><td>(17.3,21,22,22,4,23,2,0.5)</td><td>(17.2,21.2,22.4,23.1,26.8,0.4)</td></tr>
<tr><td>$\widetilde{CS}_1$</td><td>$\widetilde{CS}_2$</td><td colspan="2">$\widetilde{TB}$</td></tr>
<tr><td>(11.5,15.2,15.6,17.8,26.6,0.8)</td><td>(13.5,15.2,16.5,19.1,27.5,0.9)</td><td colspan="2">(62537635, 63624375, 64827922,83094373,886253730.6)</td></tr>
<tr><td colspan="2">$\widetilde{CCT}$</td><td colspan="2">$\widetilde{PRF}$</td></tr>
<tr><td colspan="2">(4826570,4987540,5157759,5337680,6217999,0.8)</td><td colspan="2">(87933,87919,87940,87943,87948,0.7)</td></tr>
<tr><td colspan="2">$\tilde{a}_1$</td><td colspan="2">$\tilde{a}_2$</td></tr>
<tr><td colspan="2">(7975675, 8856764, 9615578, 9836575, 12532209,0.7)</td><td colspan="2">(6975675,7856764,8615578,8836575,10486780,0.8)</td></tr>
<tr><td colspan="2">$\tilde{a}_3$</td><td colspan="2">$\tilde{a}_4$</td></tr>
<tr><td colspan="2">(7974675,8855764,9614578,9835575,11149366,0.6)</td><td colspan="2">(8572797,8856764,9615578,9836575,12532209,0.5)</td></tr>
<tr><td colspan="2">$\tilde{b}_1$</td><td colspan="2">$\tilde{b}_2$</td></tr>
<tr><td colspan="2">(823559,833559,84559,853789,863789,0.6)</td><td colspan="2">(854674,864674,876674,964674, 1156616,0.5)</td></tr>
<tr><td colspan="2">$\widetilde{CCP}_1$</td><td colspan="2">$\widetilde{CCP}_2$</td></tr>
<tr><td colspan="2">(78976, 79864, 81037, 82754, 99600,0.5)</td><td colspan="2">(659760, 798640, 880370, 852899, 996000,0.8)</td></tr>
<tr><td colspan="2">$\widetilde{CCL}_1$</td><td colspan="2">$\widetilde{CCL}_2$</td></tr>
<tr><td colspan="2">(482657,498754,515348,528756,661670,0.6)</td><td colspan="2">(482657,498754,56534,837756,851800,0.5)</td></tr>
<tr><td colspan="2">$\widetilde{CCL}_3$</td><td colspan="2">$\widetilde{CCL}_4$</td></tr>
<tr><td colspan="2">(482657,572581,665348,837756,851800,0.8)</td><td colspan="2">(873540,886340,975910,988836,1183754,0.7)</td></tr>
<tr><td colspan="2">$\widetilde{DP}_1$</td><td colspan="2">$\widetilde{DP}_2$</td></tr>
<tr><td colspan="2">(8438,8759,8789,8895,8996,0.6)</td><td colspan="2">(9012,9122,9215,9345,9474,0.5)</td></tr>
</table>

objective in constraint by picking suitable limits as shown below. The steps mentioned here were conducted to attain solution of the MOMLSTM considered in this paper:

- Step 1: Select objective function maximizing profit as the main objective (Note: The target audience for the model is enterprises taking tender of landfill clearing).
- Step 2: Solve the entire MOMLSTM problem with considering only one objective and hiding other objectives. Find minimum and maximum value of these two objectives and store as CE^{min}, CE^{max}, $time^{min}$, and $time^{max}$ respectively.
- As per the literature mentioned in [78] for the problem when primary objective is chosen as maximizing the resulting form is
  Max Profit
  Subject to constraints
  $CE \geq SS2$
  $Time \geq SS3$
  constraints eq (4)-(14)
  Here, $CE^{min} \leq SS2 \leq CE^{max}$
  and $Time^{min} \leq SS3 \leq Time^{max}$

  Prior to availing the above three steps for MOMLSTM stated in subsection E of section III, defuzzification is done using technique present in subsection B of section IV. The model is solved using LINGO optimizing software and executed on workstation equipped with an 11[th] generation Intel(R) (TM) i9 @ 3.20 GZ processor and 64.00 GB RAM. The solution attained after applying the compromise solution technique yields Profit = 3661794000, CE = 4458675, and time = 3981205, and the allocations are shown in Figure.10; it can be validated that the results attained from GAOR are better than traditional techniques like ECM.

C. VALIDATION OF PERFORMANCE OF GAOR USING PRIOR LITERATURE

The results attained using GAOR in subsection A of section VI are already validated using ECM in subsection B of section VI. However, further validation of performance of GAOR for some other multi-objective solid transportation problem (MOSTP) is performed in this text. The analysis is performed on the problem taken from [79]. The problem stated in section 4.3 is solved using inputs from section VI-A of [79]. As per the results from the literature the Total cost= 751.72\$ and total response time = 137.3(*hrs*) refer Table 7 of [79]. However, the results attained from GAOR are Totalcost = 738.72\$ and total response time = 129.6(hrs) which are comparatively better than the results from previous literature.

The new allocation results are shown in Table 13. This comparative analysis further supports the performance of GAOR over traditional GA algorithm. Thus, this research demonstrates the efficiency and usefulness of GAOR technique, demonstrating its capacity for dealing with related optimization problems.

D. PARAMETER SENSITIVITY ANALYSIS

In this section, the impact of each parameter on the three objectives of the model is explained. Understanding the

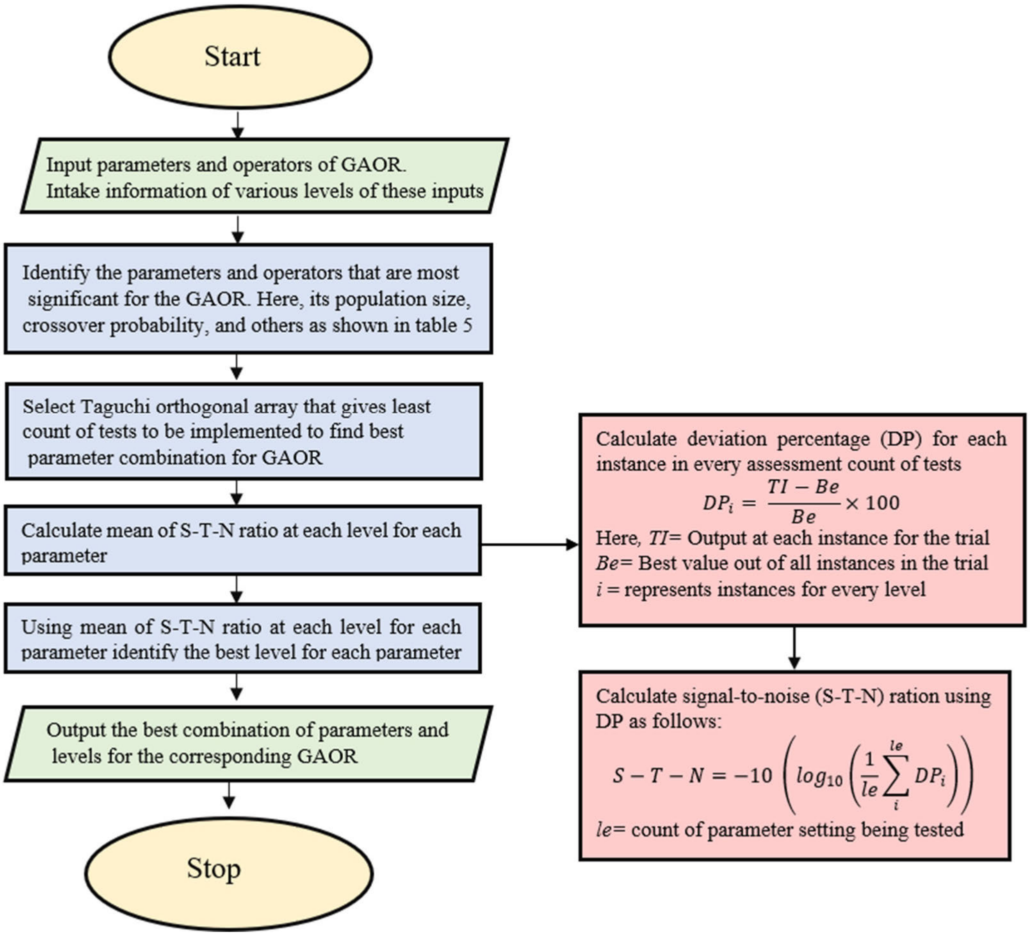


FIGURE 8. Steps for implementing Taguchi experiment in GAOR.

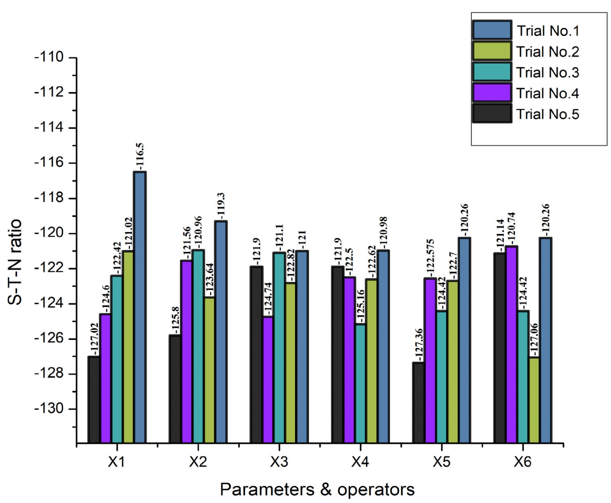


FIGURE 9. Mean of S-T-N ratio for every parameter at each level.

potential hazards and unpredictability related towards a model requires sensitivity analysis.

Industries may improve how they make decisions and create adaptive approaches to succeed by looking at several scenarios and evaluating how changes in factors affect results. The aim of this analysis is to study the impact of each cost contribution factor, carbon emitting factor, and time-consuming factor on the overall profit, carbon emission and time. The followings steps were taken to carry out a parameter sensitivity analysis in the paper:

- Step1: The first objective involving maximizing profit depends directly on various cost associated during the entire process i.e., prefeasibility cost ($\widetilde{PFS}$), Spraying bio inoculum cost ($\widetilde{SBI}$), collection cost ($\widetilde{CC}_{ijk}$), systematic excavation cost ($\widetilde{SED}$), processing cost ($\widetilde{CC}_{ijk}$), segregation cost ($\widetilde{SS}_{ij}$) Transportation cost (Processing-demand site) ($\widetilde{TCT}_{jmk'}$), processing cost $\left(\widetilde{PP}_{ij}\right)$, Transportation cost (Dumpsite-processing site) ($\widetilde{TC}_{ijk}$), and Inventory cost ($\widetilde{I}_{jl}$). Here, each cost is increased in interval of 5% within the range of $5\% - 25\%$ and change in profit is examined. The subsequent change in profit is plotted in graph in Figure. 11.
- Step 2: In second objective function the aim is to minimize carbon emission to make the process more sustainable and factors contributing towards carbon emission are landfills ($\widetilde{CL}$), segregation and sorting of waste ($\widetilde{CS}_j$), excavation ($\widetilde{TED}$), inventory ($\widetilde{CI}_{jl}$),

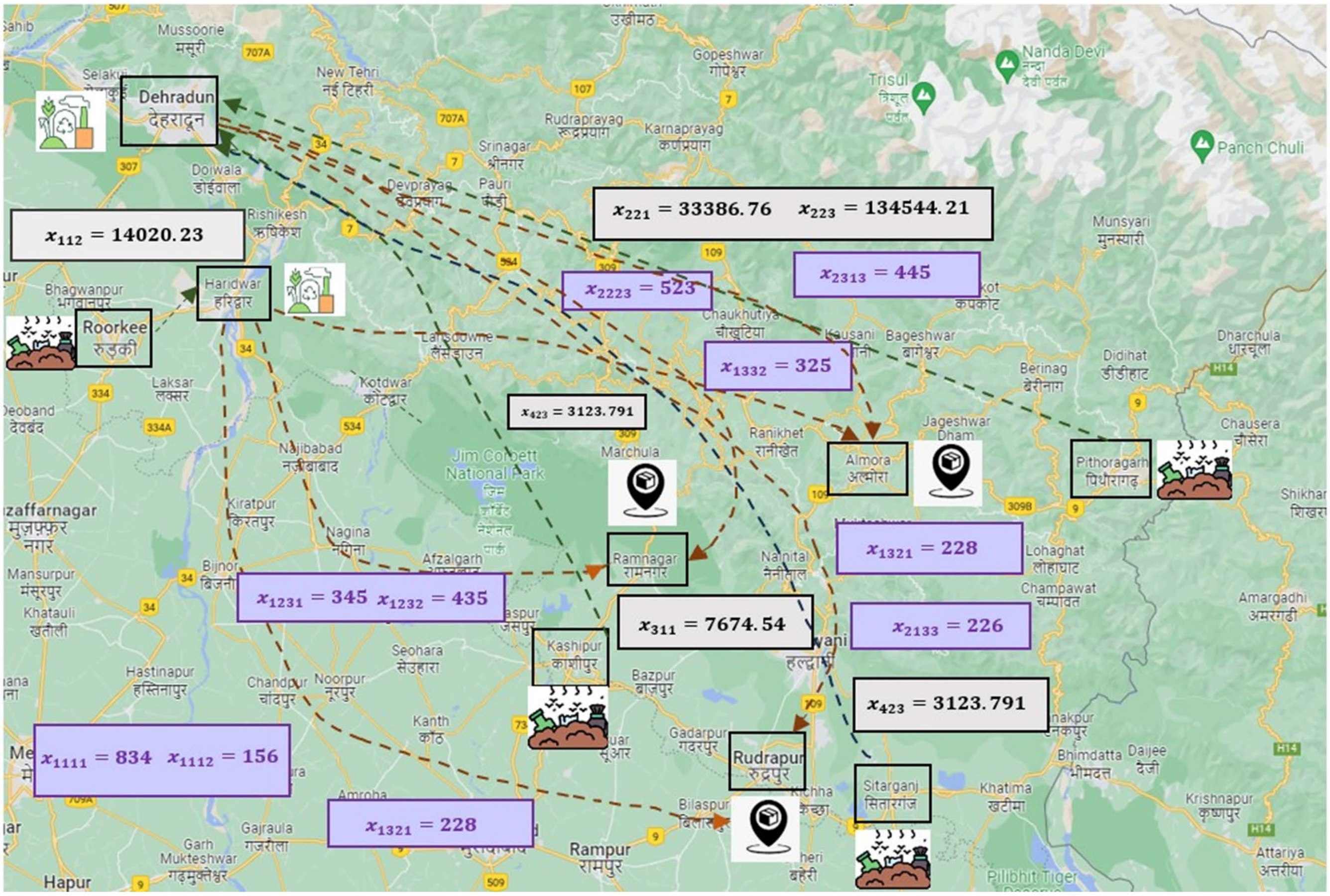


FIGURE 10. Map of the area of observation under case study along with the allocations from epsilon-constrain metho.

transportation (Processing Plant-Demand point) ($\widetilde{CTT}_{jmk'}$), transportation (Landfill-Processing plant) ($\widetilde{CT}_{ijk}$), processing ($\widetilde{CP}_j$). Here, each factor is increased in interval of 5% within the range of $5\% - 25\%$ and change in carbon emission is examined. The subsequent change in carbon emission is plotted in graph in Figure 12.

- Step 3: In third objective each time impacting factor is examined for its impact on overall time. The factors for which sensitivity is examined are prefeasibility study ($\widetilde{TPF}$), spraying bio inoculum ($\widetilde{TSB}$), sorting and segregation ($\widetilde{TSS}_j$), processing ($\widetilde{TPP}_{ij}$), excavation ($\widetilde{TED}$), transportation (Landfill-Processing plant) ($\widetilde{TT}_{ijk}$), transportation (Processing Plant-Demand point) ($\widetilde{TTT}_{jmk'}$).Here, each factor is increased in interval of 5% within the range of $5\% - 25\%$ and change in time is examined. The subsequent change in time is plotted in graph in Figure. 13.

  Post analyzing the graphs attained through sensitivity analysis it is evident that in context of profit the most sensitive parameter is $\widetilde{PP}_{ij}$. However, $\widetilde{SED}$ and $\widetilde{SBI}$ show distant behavior in different range of their increment, say for instance when the $\widetilde{SED}$ is increased by 5%, 10%, 15%, and 25%, the profit is more as compared to similar increase in $\widetilde{SBI}$; whereas at 20% the case is vice versa. $\widetilde{SS}_{ij}$ has lower impact on the profit as compared to $\widetilde{PP}_{ij}$, $\widetilde{SED}$, and $\widetilde{SBI}$ for all tested cases. Within $\widetilde{TC}_{ijk}$ and $\widetilde{I}_{jl}$ for 5% and 15% the former has less impact on profit as compared to later and for 10%, 20%, and 25% it is vice versa. Post this the decreasing order in which the impact of each cost over profit can be determined is collection $\widetilde{PFS}$, and $\widetilde{TCT}_{jmk'}$. The reason that $\widetilde{TCT}_{jmk'}$ is least impactful here is as processing plant and demand point lies near to each other.

The major contributor of carbon emission are landfills $\widetilde{CL}$ this is because whenever biodegradable trash such as leftovers from cooking, garden debris, and other types of organic substances, are dumped in dumps, they go through an anaerobic breakdown, an event that takes place refraining from oxygen, which leads to the production of gases like methane. Leachate, a fluid produced by rainwater penetrating the garbage, is another fluid produced by landfills. Leachate additionally generates further methane when it comes into touch with anaerobic situations. Post landfill the major contributor of carbon emission is waste processing $\widetilde{CP}_j$ followed by $\widetilde{CS}_j$, $\widetilde{CT}_{ijk}$, $\widetilde{CTT}_{jmk'}$, $\widetilde{CE}$, and $\widetilde{CI}_{jl}$.

TABLE 10. Factors with corresponding levels and values for Taguchi experiment.

Parameters & operators	Level & values
Population size (X1)	1 →25
	2 →50
	3 →75
	4 →100
	5 →125
Crossover probability (X2)	1 →0.5
	2 →0.6
	3 →0.7
	4 →0.8
	5 →0.9
Mutation probability (X3)	1 →0.04
	2 →0.07
	3 →0.1
	4 →0.13
	5 →0.16
	1 →Stochastic universal Sampling
Parent selection method (X4)	2 →Tournament selection
	3 →The truncation selection
	4→Roulette wheel selection
	5 →Rank selection method
Crossover type (X5)	1 → Uniform crossover
	2 → Arithmetic crossover
	3 → Cycle crossover
	4 → Single-point
	5 → Two-point
Mutation type (X6)	1 → Swap mutation
	2 → Inversion mutation
	3 →Insertion mutation
	4 →Bit flip mutation
	5 →Gaussian mutation

TABLE 11. L25 orthogonal array for Taguchi experiment.

Trial No.	X1	X2	X3	X4	X5	X6	S-T-N ratio
1	1	1	1	1	1	1	-129.9
2	1	2	2	2	2	2	-125.4
3	1	3	3	3	3	3	-123.9
4	1	4	4	4	4	4	-134.3
5	1	5	5	5	5	5	-121.6
6	2	1	2	3	4	5	-131.7
7	2	2	3	4	5	1	-122.0
8	2	3	4	5	1	2	-126.2
9	2	4	5	1	2	3	-122.8
10	2	5	1	5	3	4	-120.3
11	3	1	3	1	2	4	-126.2
12	3	2	4	2	3	5	-112.3
13	3	3	5	3	4	1	-117.4
14	3	4	1	3	5	2	-126.9
15	3	5	2	4	1	3	-129.3
16	4	1	4	2	5	3	-129.6
17	4	2	5	3	1	4	-131.6
18	4	3	1	4	2	5	-115.9
19	4	4	2	5	3	1	-114.4
20	4	5	3	1	4	2	-113.6
21	5	1	5	4	3	2	-111.6
22	5	2	1	5	4	3	-116.5
23	5	3	2	1	5	4	-122.9
24	5	4	3	2	1	5	-119.8
25	5	5	4	3	2	1	-111.7

Time has an enormous effect on landfill clearing; Methane production increases when garbage sits in a trash dump for an extended period, which causes environmental damage. Landfills occupy precious space that may otherwise be utilized for construction and leisure activities. Buildings and structures erected on or close to the landfill may sustain damage to their foundations as a result of the sinking, which is an event when the dump sinks. In regards to odor, vermin, and aesthetic destruction, landfill may possess a detrimental effect on the neighborhoods around them. Thus, minimizing time of landfill clearing task is of profound importance. $\widetilde{TPP}_{ij}$ covers major portion of overall time. It is observed that $\widetilde{TPF}$ and $\widetilde{TED}$ time shows different contribution. When the $\widetilde{TPF}$ rise by 5%, 10%, and 15%, it has higher impact on overall time increment as compared to $\widetilde{TED}$; and for 20% and 25% it is vice versa. The decreasing order of overall time contributor is $\widetilde{TSS}_j$, $\widetilde{TSB}$, $\widetilde{TT}_{ijk}$, and $\widetilde{TTT}_{jmk'}$.

E. MANAGERIAL INSIGHTS

The intention of this study is to provide a sustainability-focused profit-maximizing landfill clearing optimizing framework that minimizes carbon emission and time taken in the entire process. The managerial insights cover the points provided here that help in various aspects to authorities responsible for landfill clearing as mentioned below:

- ***Identification of key drivers:*** Multiple costs mentioned in model impact profit making capacity of the business. The key drivers of carbon emission in landfill clearing in decreasing order of their performance are $\widetilde{CL} > \widetilde{CP}_j > \widetilde{CS}_j > \widetilde{CT}_{ijk} > \widetilde{CTT}_{jmk'}, \widetilde{TED} > \widetilde{CI}_{jl}$. For profit depletion the role of factors in decreasing order of their contribution is $\widetilde{PP}_{ij} > \widetilde{SBI} > \widetilde{SED} > \widetilde{SS}_{ij} > \widetilde{I}_{jl} > \widetilde{TC}_{ijk} > \widetilde{CC}_{ijk} > \widetilde{PFS} > \widetilde{TCT}_{jmk'}$. Since, time plays one of the most crucial roles in landfill clearing thus the contribution percentage of each step of landfill clearing process in depleting order is

TABLE 12. Optimal result of MOMLSTM from GAOR using inputs from case study.

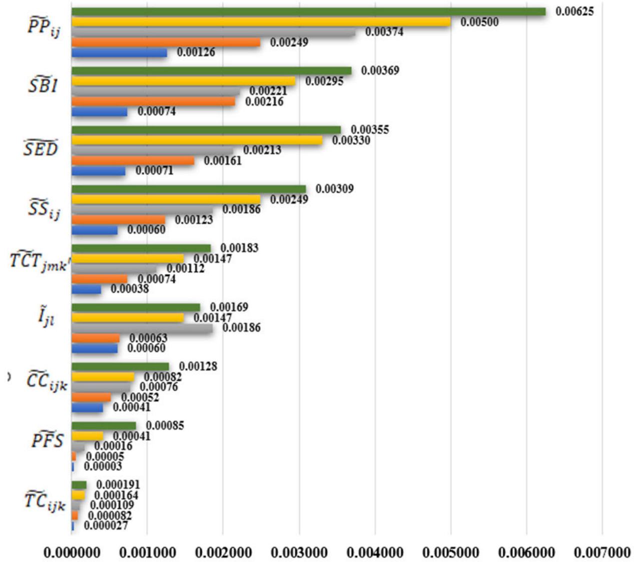
Profit = Rs. 3667156369 Time = 3834899 Carbon emission = 4401700							
Allocations ($x_{jmk'l}$)							
		$j = 1$			$j = 2$		
l	m \ k'	1	2	3	1	2	3
1	1	126	96	167	167	102	176
	2	43	65	65	60	74	38
	3	32	48	23	42	38	45
2	1	21	32	26	23	31	23
	2	54	78	97	63	65	78
	3	67	78	39	59	49	33
3	1	25	35	35	27	62	42
	2	98	96	79	55	99	96
	3	45	79	97	69	72	83
Allocations (x_{ijk})							
		$j = 1$			$j = 2$		
i \ k		1	2	3	1	2	3
1		1823	1756	1976	1423	1232	1932
2		2109	1409	1836	2235	1234	1487
3		1595	1975	1624	1246	1864	1982
4		1875	1994	1853	1523	1934	1822

TABLE 13. Allocation of relief products using GAOR for problem taken from [79].

Total cost = 738.72\$ Total response time = 129.6 (hrs)						
$k = 1$						
	$i = 1$			$i = 2$		
j	$p = 1$	$p = 2$	$p = 3$	$p = 1$	$p = 2$	$p = 3$
1	1.05	1.1	3.1	1.4	1.34	3.1
2	0.7	0.93	4.11	2.1	0.8	4.1
3	2.8	4.25	5.9	3.7	4.8	5.2
4	3.25	2.27	0.8	0.6	1.2	1.8
$k = 2$						
1	0.98	0.3	2.4	1.4	1.2	0.8
2	1.1	0.56	4.5	1.7	1.3	2.9
3	1.7	6.1	2.0	2.8	3.9	5.6
4	2.7	6.9	0.4	2.1	2.8	2.5

$\widetilde{\text{TPP}}_{ij} > \widetilde{\text{TED}} > \widetilde{\text{TPF}} > \widetilde{\text{TSS}}_j > \widetilde{\text{TSB}} > \widetilde{\text{TT}}_{ijk} > \widetilde{\text{TTT}}_{jmk'}$. Note: This examining is for maximum increase in each cost as shown in sensitivity analysis.

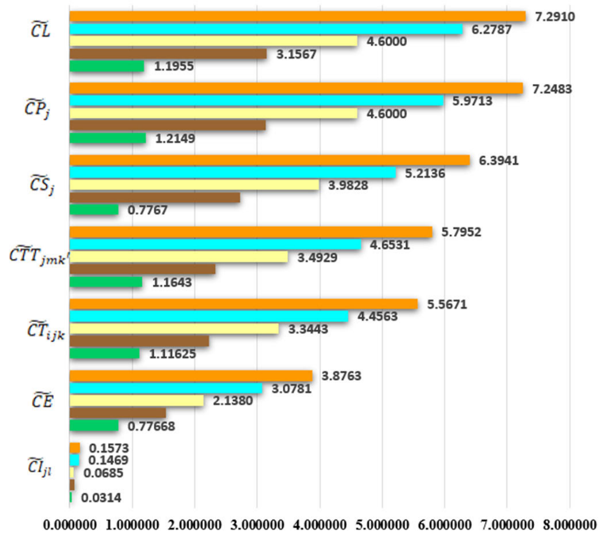
- ***Budget planning of assorted expenses:*** It is observed that profits are impacted most by the increase in waste processing cost as compared to other costs. To be precise $\widetilde{\text{CC}}_{ijk}$, has maximum i.e., 69.62% more impact on profit reduction as compared to $\widetilde{\text{SBI}}$. Some preventive measures that can be taken by the authorities to decrease waste processing costs include introduction of automation and robotics to reduce labor cost, continuous waste



	$\widetilde{TC}_{ijk}$	$\widetilde{PFS}$	$\widetilde{CC}_{ijk}$	$\tilde{I}_{jl}$	$\widetilde{TCT}_{jmk'}$	$\widetilde{SS}_{ij}$	$\widetilde{SED}$	$\widetilde{SBI}$	$\widetilde{PP}_{ij}$
25%	0.000191	0.00085	0.00128	0.00169	0.00183	0.00309	0.00355	0.00369	0.00625
20%	0.000164	0.00041	0.00082	0.00147	0.00147	0.00249	0.00330	0.00295	0.00500
15%	0.000109	0.00016	0.00076	0.00186	0.00112	0.00186	0.00213	0.00221	0.00374
10%	0.000082	0.00005	0.00052	0.00063	0.00074	0.00123	0.00161	0.00216	0.00249
5%	0.000027	0.00003	0.00041	0.00060	0.00038	0.00060	0.00071	0.00074	0.00126

Percentage increase in each cost ■ 25% ■ 20% ■ 15% ■ 10% ■ 5%

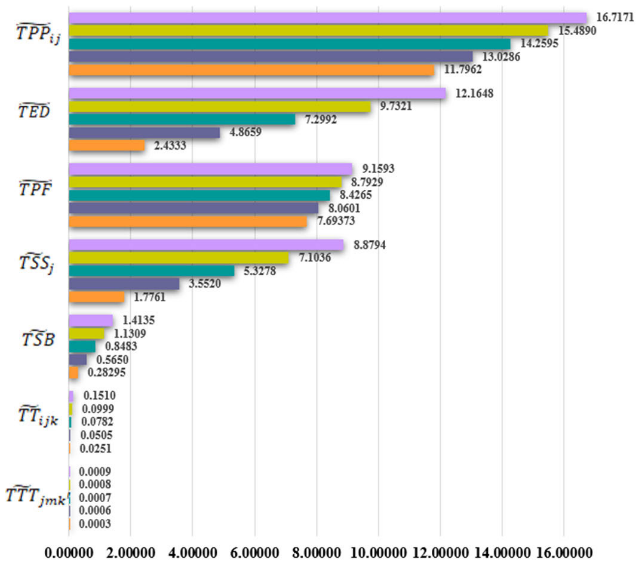
FIGURE 11. Parameter sensitivity analysis for profit objective showing the involvement of different costs in profit.



	$\widetilde{CI}_{jl}$	$\widetilde{CE}$	$\widetilde{CT}_{ijk}$	$\widetilde{CTT}_{jmk'}$	$\widetilde{CS}_j$	$\widetilde{CP}_j$	$\widetilde{CL}$
25%	0.1573	3.8763	5.5671	5.7952	6.3941	7.2483	7.2910
20%	0.1469	3.0781	4.4563	4.6531	5.2136	5.9713	6.2787
15%	0.0685	2.1380	3.3443	3.4929	3.9828	4.6000	4.6000
10%	0.0731	1.5395	2.2310	2.3286	2.7203	3.1396	3.1567
5%	0.0314	0.77668	1.11625	1.1643	0.7767	1.2149	1.1955

Percentage increase in components contributing towards carbon emission ■ 25% ■ 20% ■ 15% ■ 10% ■ 5%

FIGURE 12. Parameter sensitivity analysis for carbon emission showing the contribution of various factors in overall carbon emission.



	$\widetilde{TTT}_{jmk'}$	$\widetilde{TT}_{ijk}$	$\widetilde{TSB}$	$\widetilde{TSS}_j$	$\widetilde{TPF}$	$\widetilde{TED}$	$\widetilde{TPP}_{ij}$
25%	0.0009	0.1510	1.4135	8.8794	9.1593	12.1648	16.7171
20%	0.0008	0.0999	1.1309	7.1036	8.7929	9.7321	15.4890
15%	0.0007	0.0782	0.8483	5.3278	8.4265	7.2992	14.2595
10%	0.0006	0.0505	0.5650	3.5520	8.0601	4.8659	13.0286
5%	0.0003	0.0251	0.28295	1.7761	7.69373	2.4333	11.7962

Percentage increase in components contributing towards time   25% 20% 15% 10% 5%

FIGURE 13. Parameter sensitivity analysis for time highlighting contribution of various steps of landfill mining.

audits and plant performance monitoring, frequent cost benefit analysis. Implementation of regular maintenance schedules. For reducing impact of $\widetilde{SBI}$ that has 3.84% more impact on profit as compared $\widetilde{SED}$ to that has few measures such as advocating the application of concentrated bio-culture is advantageous as it produces notable outcomes with little effort; figuring out the best times and intervals for spraying; improving the effectiveness of sprinkling apparatus; permitting within the farm bio- inoculum manufacturing; and offering government financing for bio- inoculum supplies are all profitable projects. The other factors $\widetilde{SS}_{ij}$, $\widetilde{I}_{jl}$, $\widetilde{TC}_{ijk}$, $\widetilde{CC}_{ijk}$, $\widetilde{PFS}$, and $\widetilde{TCT}_{jmk'}$ does not show much variation on their impact on profit. However, some crucial measures that can reduce these costs are Routing optimization, transportation expense bargaining, software for stock control utilization, employee education, and market projections are all ways to prevent stockouts and overloading of inventories.

- ***Incorporation of sustainability for long lasting impact:*** Sustainability inclusion is of vital importance for enterprises implementing this concept into their landfill cleaning operation. Businesses prioritizing sustainability are more capable of adapting to changing marketplace circumstances and regulatory requirements. Furthermore, these companies are more likely to follow regulations aimed at protecting the environment, lowering their chance of facing fines and other legal repercussions. The major source of emission in the entire process is emission from landfills $\widetilde{CL}$ followed by emission during waste processing $\widetilde{CP}_j$. To enumerate they are responsible for 14.02% and 13.36% more emission as compared to segregation and sorting technique. The installation of an anaerobic fermentation infrastructure, which traps the methane gas released throughout decomposition, may lower pollutants from dumps. Mechanisms for harvesting methane could be put in place to use the gas to produce energy. By further reducing the volume of oxygen inside the dump, impenetrable coverings and obstacles can help lessen emissions. Power-efficient cooling and heating as well as lighting solutions, should be implemented at garbage treatment establishments to reduce power usage and the ecological impact that results from it. Leveraging sustainable sources of energy, including plant matter, solar power, or wind power, can significantly reduce GHGs release. The damaging environmental impact due to carbon emission from other steps $\widetilde{CS}_j$, $\widetilde{TED}$, $\widetilde{CI}_{jl}$, $\widetilde{CTT}_{jmk'}$, and $\widetilde{CT}_{ijk}$, of landfill clearing can be reduced by investing good amount in carbon offsetting projects, continuous innovation and upgradation in methodology, consolidation of load, route optimization, educating staff.
- ***Time critical adherences and deadline driven goals:*** The major time taking activity i.e., waste processing takes ($\widetilde{TPP}_{ij}$) 37.42% more time than waste excavation ($\widetilde{TED}$), which in return takes 32.81% more time than prefeasibility study ($\widetilde{TPF}$). Because of their adverse impacts on the planet, the scarcity of available land, and legal requirements, landfills must be promptly cleared. Investment in automated machines, identification of bottlenecks, parallel processing, and frequent maintenance of equipment can reduce lot of processing time. In order to reduce $\widetilde{TED}$ following measures can be taken, comprehensive site evaluation, special care of safety, explicit dump identification, and up to date devices. Other measures that should be taken to reduce $\widetilde{TSB}$, $\widetilde{TSS}_j$, $\widetilde{TT}_{ijk}$, and $\widetilde{TTT}_{jmk'}$ are optimizing route, efficient labor, penalties for delay, and awareness among population.

VIII. CONCLUSION AND FUTURE SCOPE

Landfill locations are visually unappealing, but the concerns extend far beyond the unsightliness of extensive waste heaps. The disposal of waste in landfills gives rise to various health and environmental problems, including the release of dangerous pollutants, the formation of leachate, the emission of GHGs, and the occurrence of frequent fires. Consequently, the foremost goal of each government at present is not solely to decrease waste generation but also to address the existing waste in landfills. The waste deposited in these landfills possesses substantial financial possibilities, with the potential to yield numerous value-added products through appropriate processing. Nevertheless, the crux of the matter is that there is a significant demand for innovative ideas and research concerning profitable landfill clearing methods that effectively control carbon emissions while being time-efficient. Therefore, this research paper proposed an optimization framework for landfill mining using MOMLSTM (Maximize Profit, Minimize Carbon Emission, and Time-efficient Process). The model incorporates cost, time, and carbon emission parameters throughout key stages of landfill mining, including waste analysis, excavation, bio-inoculation, collection, sorting, processing, and transportation. To enhance the practical applicability of this model in real-world scenarios, various uncertainties are accounted for using PFN. Subsequently, an up-to-date defuzzification technique is employed to convert the model into a precise format. To assess the real-life implications of the model, a case study is conducted.

The research paper also proposed a novel technique to solve MOMLSTM called as GAOR. This GAOR algorithm is created by incorporating an offspring refinement step after the mutation in the GA. To determine the most optimal parameter settings for GAOR, the well-known Taguchi experiment was conducted. Through an analysis of different combinations of parameter settings, the most efficient selections for crossover type, crossover probability, mutation type, mutation probability, population size, and parent selection method were identified. Using the Taguchi experiment it was found that the most negative mean S-T-N ratio for $X1$, $X2$, $X3$, $X4$, $X5$, and $X6$ are -127.02, -125.8, -124.74, -125.16, -127.36, and -127.06 respectively. As a result, the best parameter setting for GAOR is $X1 = 125$, $X2 = 0.9$, $X3 = 0.13$, $X4$ is truncation selection, $X5$ is two-point crossover, and $X6$ is inversion mutation.

Three critical performance metrics—IGDX, PSP, and HV were used to gauge the GAOR's performance over 24 test cases from the CEC 2020 assessment suite. Then, the performance of GAOR was contrasted with six well-known MOO algorithms. GAOR outperformed MOEOSMA, EMOPSO, MOGTO, ASDMSGA-II, MOSMA, and MEOA according to the findings of a statistical evaluation, the FMR test. Moreover, by utilizing the Wilcoxon test, it was shown that the results acquired through GAOR were not arbitrary and had noteworthy consequences for each of the three measures. Furthermore, a more detailed analysis of the box plots for the twenty PSP value iterations showed that GAOR had the best box plot with the fewest outliers and the most prominent and tightest clustering. This finding highlights the effectiveness of the algorithm by indicating a striking similarity between the computed solutions and the actual Pareto set.

The research paper's analysis of MOMLSTM, coupled with the GAOR approach, compared its outcomes to those generated by the ECM method. The results revealed that GAOR led to resource allocations that could enhance the profitability of LFM in the Uttarakhand region by 0.14%. Moreover, it exhibited the potential to reduce overall carbon emissions by 1.29% and decrease the time required by 3.81%. GAOR's notable strength lies in its capacity to find the optimal balance between intensification and diversification efforts, which is achieved by incorporating a refinement process for offspring using LS. Additionally, GAOR demonstrates adaptability in navigating the search space, enabling it to strike a harmonious equilibrium between local and global search strategies while adapting to the solution space's topology. Nevertheless, it is worth noting that GAOR does have certain limitations, including increased algorithm complexity, which may necessitate additional parameter tuning, and the potential for further improvement in terms of time complexity.

After conducting a comprehensive sensitivity analysis, it is evident that to optimize profit, one must effectively manage processing costs with state-of-the-art technology, skilled manpower, and regular servicing and maintenance of processing equipment. Regarding carbon emission, the primary contributor is the waste in landfills; thus, the installation of proper methane trapping systems and impermeable covers in landfills becomes crucial in mitigating carbon emissions. Nevertheless, to reduce the time required for landfill clearing, one can accelerate waste processing by incorporating advanced automated tools and a more efficient workforce. Numerous opportunities for future research exist, such as extending the model to address the rehabilitation of vacant landfill sites and exploring the use of type-2 fuzzy for input parameters. Additionally, a mathematical model that incorporates diverse revenue streams, including industrial enhancements, market feedback, and environmentally friendly practices, could be developed.

CONFLICT OF INTEREST

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