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Solid waste recycling and management cost optimization algorithm

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ABSTRACT

Solid waste is a major issue in today's world. Which can be a contributing factor to pollution and the spread of vector-borne diseases. Because of its complicated nonlinear processes, this problem is difficult to model and optimize using traditional methods. In this study, a mathematical model was developed to optimize the cost of solid waste recycling and management. In the optimization phase, the salp swarm algorithm (SSA) is utilized to determine the level of discarded solid waste and reclaimed solid waste. An optimization technique SSA is a new method of finding the ideal solution for a mathematical relationship based on leaders and followers. It takes a lot of random solutions, as well as their outward or inward fluctuations, to find the optimal solution. This method also included multiple adaptive and random variables to guarantee that the solution space was explored and used in various optimization tasks. When all criteria are considered, the results of this study show that the SSA is efficient for least-distance path allocation. The simulation findings reveal a significant improvement over the well-known particle swarm optimization (PSO) algorithm, with recycling and disposal costs decreasing by 10% to 30%.

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1. INTRODUCTION

The number of industries in the modern world is rapidly increasing to meet the demands of a rapidly growing population. Solid waste is generated mostly by factories and human activities in daily life, and its management normally entails regulating its storage, collection, transportation, recycling and reuse, processing, and disposal in accordance with public health, economic, and environmental concerns [1], [2]. The primary objective of solid waste management (SWM) is to mitigate the negative environmental implications of indiscriminate solid waste disposal. This study focuses on solid waste collection, which is a vital component of sustainable waste management [3]-[5].

In this research, two SWM processes were identified: waste recycling and disposal. Recycling is the act of converting waste resources into useable commodities in order to lower production costs. SWM includes collecting waste at the source, keeping it for proper management, processing it, recycling what can be recycled, and eventually disposing of the remainder of the garbage. SWM's two main operations are recycling and disposal. Waste is disposed of when the remaining waste has no value and is no longer used in any manufacturing process [6], [7].

The other study [8] uses an Arduino Mega to develop a system for automatically sorting recyclable metal household garbage into four categories: aluminium, non-metallic, copper, and steel. The research concentrated on metal resources since they are the most valuable since they are easily recoverable and have the highest monetary value in comparison to other recyclable materials. In this work [9], an algorithm is proposed to use properties of recyclable waste such as size and weight. The parameters are determined using the weight sensor and ultrasonic sensors and the algorithm classifies the things based on the data contained in the available database. Furthermore, the study [10] employed a genetic algorithm, which took into account the following factors: (multiple vehicles, recycling stations to refill capacity, and truck capacity). Where are no truck moves to an empty waste site and the vehicle is sent to a route where the quantity of garbage does not exceed the truck's capacity (it will proceed to a nearby recycling station and then to another location), thus optimizing the number of trucks needed in a given region.

In another paper [11], the model was solved using a heuristic technique based on simulated annealing (SA). In a typical industrial solid waste recycling process, a combinatorial optimization approach was applied. To find the most appropriate recycling approach and production pattern. Together with the number and pattern of items that match this approach in order to maximize marginal earnings. The authors of the study [12] built a dynamic optimization model that was integrated into a geographic information system-based (GIS-based) system for managing solid waste recycling in the municipality of Cogoleto (Italy). The model considers a variety of materials and trucks for solid waste collection. It optimizes daily material recycling in order to save expenses and increase profit on material sales. The Scine-Cosine algorithm (SCA) is utilized in this work [13] to solve the solid waste recycling problem. Which is a population-inspired heuristic designed for solving optimization problems. The SCA is dependent on the sine-cosine mathematical function. It employs these functions to efficiently explore and utilize the solution space between two solutions in an effort to discover superior solutions in the solution space. Sarwar *et al.* [14] develops a mathematical model for minimizing the cost of solid waste management. For optimum performance particle swarm optimization (PSO) is used to determine the level of solid waste discarded and solid waste recycled. Another meta-heuristic method known as the genetic algorithm (GA) is utilized to evaluate the effectiveness of PSO output. The optimal solutions generated by PSO and GA algorithms are nearly identical. The difference between these two optimal objective function values is negligible (2.5%).

The goal of this project is to develop mathematical models that account for the expenses of recycling and disposing of waste. The models were optimized using the salp swarm approach (SSA), a population-based approach. It is an extremely effective method for resolving real-world problems involving unknown spaces. SSA is a nature-inspired algorithm that mimics the swarming behaviour of Salps while they navigate and hunt in seas [15]. The most notable aspect of this study is the first attempt to apply the SSA to reduce industrial recycling and trash disposal costs.

2. OPTIMIZATION PROBLEMS AND ALGORITHMS

There are hundreds, if not thousands, of optimization problems in the scientific and technical domains. Certain of these problems lack an ideal solution, a method for discovering the optimal solution, or an algorithm for finding the optimal solution in deterministic time; thus, they are referred to as non-deterministic polynomial time (NP) problems. They are often divided into two types based on whether they are containing constrained or unconstrained. The following equations provide a generalized mathematical formulation for these problems:

$$Min/Max\ f_n(X) = \{i = 1,2,3,4,5, \dots D\} \tag{1}$$

$$S.T\ \ p_t(x) \leq 0\ \{t = 1,2,3,4,5, \dots, t\} \tag{2}$$

$$o_e(x) = \ 0\ \{e = 1,2,3, 4,5, \dots, e\} \tag{3}$$

The fitness function is denoted by $f_n(x)$, where $p_t(x)$ and $o_e(x)$ denote the optimization problem's inequality and equality constraints. Finally, x denotes a vector of decisions variables. The amount of variables that can be chosen has an impact on the problem itself, and there are problems divided into small (fewer than 100 choice variables) and those on a big scale (more than 100 decision variables). In certain circumstances, these issues have hundreds of choice factors, which complicate the search procedure.

Numerous optimization algorithms have been presented over the last few decades to solve similar challenges. Since they replicate or mimic natural phenomena such as firefly flashes, grey wolf hunting strategies, and bird flight, for example, the bulk of these algorithms were inspired by nature [16]. Several of the algorithms described were inspired by mathematical equations, for example, the SCA [17]. Additionally, there are algorithms that are inspired by physical phenomena, such as the movement of nomads in the desert when they seek out better positions near water sources, the black hole (BH) algorithm which simulates the universe's black hole [18]–[20]. Metaheuristics success has attracted academics from a variety of sectors to solve optimization challenges. Researchers in the field of machine learning have employed a range of metaheuristics to enhance their prediction models across a variety of case studies [21]–[24]. Additionally, this approach has been used to tackle engineering challenges [25], [26]. Using metaheuristics, researchers have also attempted to solve feature selection difficulties, a common optimization problem in data science [27].

Any multi-solution optimization based on the population of solutions approach may be influenced by two crucial components: global search capability and exploitation or local search capability. Both of these components are critical to the search process. These two components should be adjusted appropriately for the optimization problem at hand. Increases in one search capability at the expense of another can delay the search process or may cause the algorithm to get stuck in local optima [28], [29]. The following section goes into detail about the solid waste collecting problem, which is formulated as a problem of optimization.

3. PROBLEM FORMULATION

To be green, companies must reduce trash creation, which can only be accomplished via appropriate waste management. As a result, this study investigates the solid waste management process. Among them are recycling and garbage disposal in industry. The objective is to discover various waste management criteria and use them to develop a mathematical model. Then, we combined all of the models to produce a cost-minimization goal function. Certain criteria were established during the model formulation procedure in this study to facilitate the process. They are items with independent demand rates, and the demand rates remain constant throughout time without volume decline. The following can be used to define the objective function (4):

$$Z = \alpha \sum Lr_i \, D_i \, Cr_i + \beta \sum Ld_i \, D_i \, Cd_i \tag{4}$$

where D_i indicates the demand for each product over a specified time period, Cr_i indicates the cost of recycling each commodity, Cd_i represents the cost of disposal for each commodity, Ud represents the maximum amount of waste that can be disposed of in a given period, Ur signifies the period's maximum amount of recycling, Lr_i indicates the amount of recycling that occurred during the specified time period, Ld_i indicates the amount of solid waste disposed of per period, W_t signifies the entire amount of solid trash generated over a specified time period, and i denotes $\{1,2,3,4 \ldots, n\}$, where n denotes the number of total elements. Moreover, α and β are calculated as shown in:

$$\alpha = \frac{\sum Lr_i \, D_i}{\sum(Lr_i \, D_i) + \sum(Ld_i \, D_i)} \tag{5}$$

$$\alpha = \frac{\sum Lr_i \, D_i}{\sum(Lr_i \, D_i) + \sum(Ld_i \, D_i)} \tag{6}$$

Two primary constraints should be considered:

$$\alpha + \beta = 1, \qquad Lr_i, Ld_i > 0$$

4. SALP SWARM OPTIMIZATION

Salps are members of the family Salpidae, their body is cylindrical and are like jellyfishes in terms of movement and texture. Figure 1(a) depicts the shape of a Salp. The movement of Salps involves pushing water backwards for it to move forward [30]. Studies on the biology of Salps are still preliminary as they normally live in environments that cannot be easily accessed and cannot be easily maintained in a laboratory. The Salp swarm algorithm was developed based on inspiration from Salps swarming attitude [15]. Salps form a swarm called Salp chain in oceans which helps them move better while foraging [31]. A depiction of the Salp chain is presented in Figure 1(b).

The mathematical model for the Salp chain was developed by splitting the Salps population into two subpopulations: leaders and followers. The leader of the chain is the leader, while the remainder is followers [32]. Determination of Salps location is done as other swarm-based techniques; this is done by an n-dimensional search space through the consideration of the number of parameters (n) in the considered problem. Hence, the position of the salps will be mapped in a 2-D matrix represented as x. Consider a solution space where "*F*", the food source, is target of the swarm. It is suggested that the position of the be upgraded using the following equation:

$$x_k^1 = \begin{cases} F_k + c_1\big((ub_k - lb_k)c_2 + lb_k\big), c_3 \geq 0 \\ F_k + c_1\big((ub_k - lb_k)c_2 + lb_k\big), c_3 < 0 \end{cases} \quad (7)$$

where x_k^1 is the position of the leader (the 1st Salp) in the k^{th} dimension, lb_k denotes the k^{th} dimension's upper and lower boundaries and F_k denote the k^{th} dimension position of the food source, ub_k, respectively while c_1, c_2, and c_3 are random parameters. The position of the leader is updated in consideration of the food source as captured in (7). c_1 is the most significant SSA parameter as it regulates the trade-off between exploration and exploitation as defined thus:

$$c_1 = 2e^{-\left(\frac{rl}{L}\right)^2} \quad (8)$$

where L denotes the maximum number of iterations and l denotes the currently iteration. c_2 and c_3 are random numbers generated evenly in the range [0,1]; both parameters dictate the alignment of the next position in j^{th} dimension (i.e., whether it should have a positive or negative infinity bias); they also determine the step size. The location of the followers is updated in the following manner in line with Newton's law of motion:

$$x_j^i = \frac{1}{2}at^2 + v_0 t \quad (9)$$

where $i \geq 2, x_j^i$ is the position of i^{th} follower Salp in j^{th} dimension, v_0 represents the initial speed, t is time, and $a = \frac{v_{fina}}{v_0}$, where $v = x - x_0/t$. Being that time is an iteration in optimization processes, the difference between iterations = 1 and if $v_0 = 0$, this equation can be represented as:

$$x_j^i = \frac{1}{2}(x_j^i + x_j^{i-1}) \quad (10)$$

where $i \geq 2$ and x_j^i represent the position of i^{th} follower Salp in the j^{th} dimension. In (1) and (4) can be used to simulate the Salp chain. The pseudocode of SSA in Figure 2, while the flowchart of the proposed SSA for segmentation by weighted aggregation (SWA) in Figure 3.

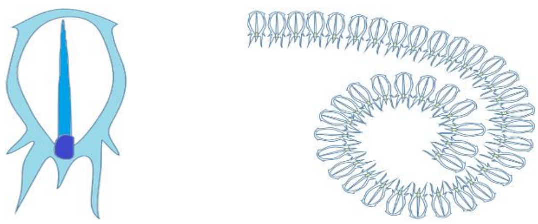

Figure 1. The swarming Salps while they navigate and hunt in seas; (a) single Salp and (b) Salps' chain

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Initialize the salp population (xi) by taking up and lb into account.
While (The end condition is not met)
  Calculate the fitness function using Eq. (4)
  F= search of best agent in population
  Utilize Eq. (8) to update c1
    For all salp (xi)
      If (I == 1)
            Using Eq. (7) to update the position of the leading salp.
       Else
            Using Eq. (10) to update the place follower salp.
      End
    End
    Modify the slaps in accordance with the variable's upper and lower bounds
End
```

Figure 2. The pseud code of SSA

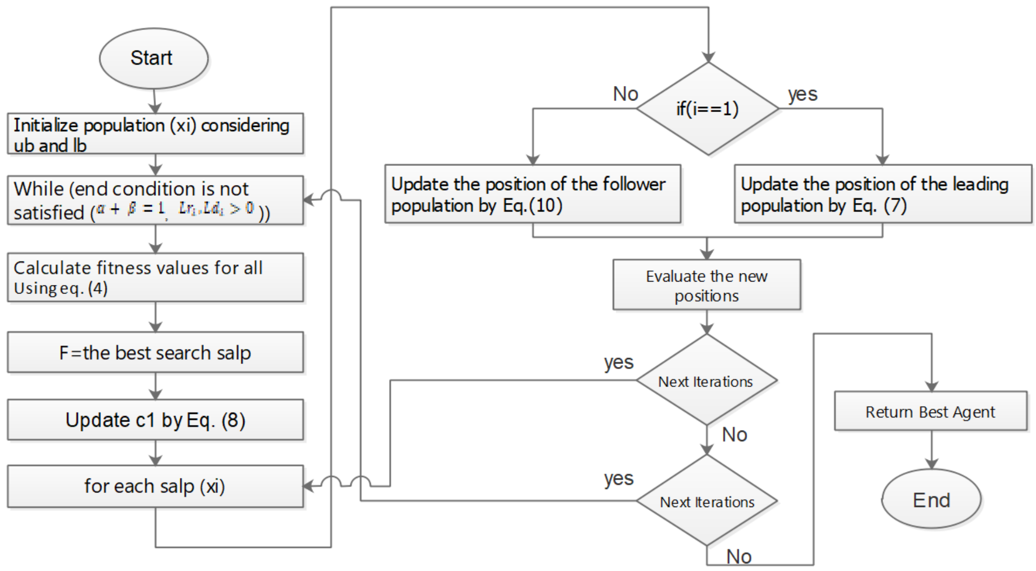

Figure 3. The flowchart of the proposed SSA for SWA

5. RESULTS AND DISCUSSION

This paper describes the creation and evaluation of the fundamental mathematical model for the optimization issue of solid waste using MATLAB version 2017b. The suggested SSA algorithm was assessed on a variety of population sizes (10, 20, 30, 40, and 50) and item counts (10, 40, and 60). To compare, the PSO algorithm was built under the identical conditions (c 1=1.42, c 2=1.42) for the same optimization issue.

The power and superiority of the PSO algorithm over other optimization techniques have been distinctly confirmed by numerous researches such as [14], [33]. Accordingly, the results in this paper have been demonstrated by comparing them with such a powerful method. The acquired findings are depicted in Figures 4-6, which demonstrate the performance of SSA when used to solve the solid waste collection problem using a variety of search agents. SSA attained more stability; in other words, its standard deviation is less than that of PSO (Std. for SSA=0.0732, Std. for PSO=1.1621). This indicates that the algorithm was fairly similar in its output, but PSO was more diverse than SSA.

The algorithm's search performance was influenced by the number of search agents. With a rise in the number of searching agents, the likelihood of discovering better opportunities increased as well. It should be noted that when the number of particles increased, PSO increased as well; however, the enhancement rates were lower than those for SSA. Notably, the worst case of SSA outperformed the best instance of PSO; this demonstrated that the paper's primary contribution had been done. Additionally, as illustrated in Figures 4-6, SSA outperformed PSO even when the number of items rose, indicating that SSA remained steady as the number of items increased.

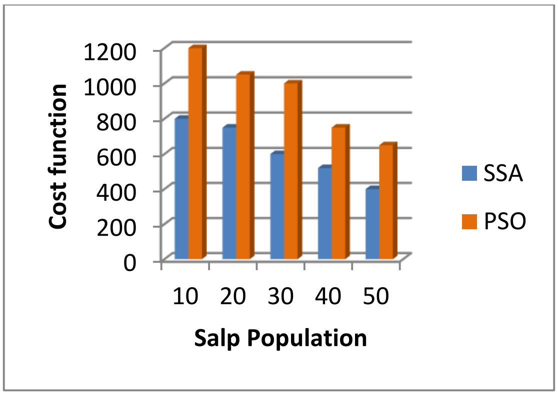

Figure 4. The best recycling and disposal expenditure obtained using SSA and PSO, where the number of item 10

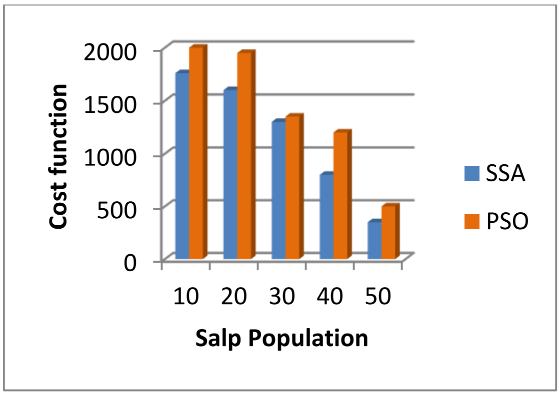

Figure 5. The best recycling and disposal expenditure obtained using SSA and PSO, where the number of an item 40

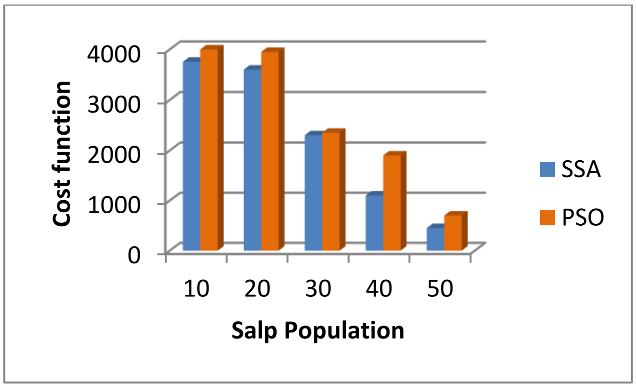

Figure 6. The best recycling and disposal expenditure obtained using SSA and PSO, where the number of item 60

Additionally, the convergence analysis of both techniques was compared. Convergence for both algorithms is shown in Figures 7-9, with SSA achieving a higher rate of convergence than PSO due to a more balanced global and local search capability. The PSO balancing mechanism, on the other hand, was primarily affected by the values of the parameters c1 and c2.

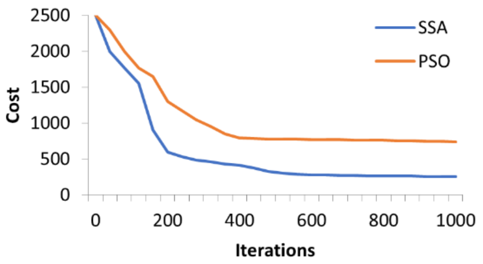

Figure 7. Convergence analysis is used to compare algorithms (count of search agents = 50 and the quantity of an item = 10)

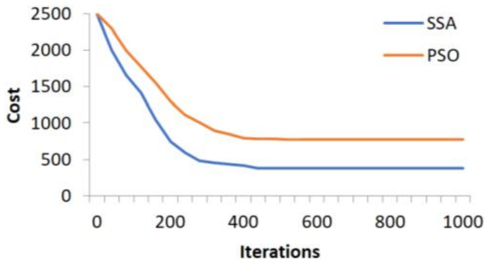

Figure 8. Comparison of the algorithms based on convergence analysis (count of search agents = 50 and the quantity of an item = 40)

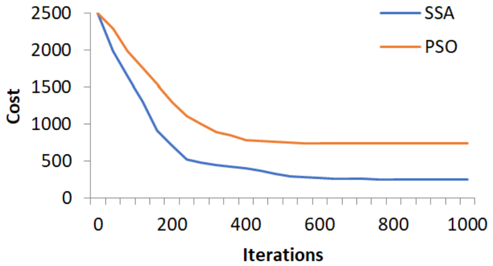

Figure 9. Comparison of the algorithms based on convergence analysis (Count of search agents = 50 and the quantity of an item = 60)

As shown in Figure 7, for the initial 200 iterations, SSA outperformed PSO; after that, the algorithm's performance improvement halted. Additionally, performance was improved till the final iteration (i. e, 1000). This result demonstrated that SSA was capable of locating the optimal solution in the best possible location and avoiding local minima.

As SSA and PSO are population-based optimizing approaches, they can be compared easily. Figure 6 representations clearly show a minor difference between the SSA and PSO approaches. It also suggests that SSA has good computational efficiency. Furthermore, SSA can be applied without hesitation to optimize any problem population-based strategy.

6. CONCLUSION

Solid waste recycling and management cost optimization was the primary focus of this study's investigation. During the optimization phase, the SSA was utilized to determine the amount of solid waste disposed of and recycled. The proposed SSA was used to combine multiple adaptive and random variables in order to ensure that the solution space was explored and exploited in a variety of optimization tasks. The SSA has been employed efficiently to determine the least-distance path while taking all considerations into account. The proposed SSA method produced a solution that was superior to the well-known PSO technique. Indicating that SSA remained steady as the number of items increased. This demonstrated that the paper's primary contribution had been done. The simulation findings reveal a significant improvement over the well-known PSO algorithm, with recycling and disposal costs decreasing by 10% to 30%. Additionally, although employing the same amount of iterations to solve the identical issue, the suggested SSA demonstrated faster convergence than the PSO. There are many possibilities for future research using the presented approach to deal with dynamic data, which is acquired by sensors in the surrounding environment.

REFERENCES

[1] F. A. Dery, E. D. Kuusaana, and E. Owusu-Sekyere, "Solid Waste Characterization and Recycling Potential for University Campuses in Ghana: Case Study of Two Ghanaian Universities," *J. Waste Recycl.*, vol. 3, no. 1, p. 3, 2018.

[2] O. M. Anssari, E. A. Alkaldy, N. Almudhaffar, A. N. Altaee, and N. S. Ali, "A feasibility study of electrical energy generation from municipal solid waste in Iraq: Najaf case study," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 4, pp. 3403–3411, Aug. 2020, doi: 10.11591/ijece.v10i4.pp3403-3411.

[3] A. M. Taha, S.-D. Chen, and A. Mustapha, "Natural Extensions: Bat Algorithm with Memory," *J. Theor. Appl. Inf. Technol.*, vol. 79, no. 1, pp. 1–9, 2015.

[4] A. M. Jasim, H. H. Qasim, E. H. Jasem, and R. H. Saihood, "An internet of things based smart waste system," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 3, pp. 2577–2585, Jun. 2021, doi: 10.11591/ijece.v11i3.pp2577-2585.

[5] A. A. I. Shah, S. S. M. Fauzi, R. A. J. M. Gining, T. R. Razak, M. N. F. Jamaluddin, and R. Maskat, "A review of IoT-based smart waste level monitoring system for smart cities," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 1, pp. 450–456, Jan. 2021, doi: 10.11591/ijeecs.v21.i1.pp450-456.

[6] X. Chen, "Machine learning approach for a circular economy with waste recycling in smart cities," *Energy Reports*, vol. 8, pp. 3127–3140, Nov. 2022, doi: 10.1016/j.egyr.2022.01.193.

[7] Q. Huang, G. Chen, Y. Wang, L. Xu, and W. Q. Chen, "Identifying the socioeconomic drivers of solid waste recycling in China for the period 2005–2017," *Science of The Total Environment*, vol. 725, p. 138137, Jul. 2020, doi: 10.1016/j.scitotenv.2020.138137.

[8] S. H. Yusoff, S. Mahat, N. S. Midi, S. Y. Mohamad, and S. A. Zaini, "Classification of different types of metal from recyclable household waste for automatic waste separation system," *Bulletin of Electrical Engineering and Informatics*, vol. 8, no. 2, pp. 488–498, Jun. 2019, doi: 10.11591/eei.v8i2.1488.

[9] N. S. Midi, M. A. Rahmad, S. H. Yusoff, and S. Y. Mohamad, "Recyclable waste separation system based on material classification using weight and size of waste," *Bulletin of Electrical Engineering and Informatics*, vol. 8, no. 2, pp. 477–487, Jun. 2019, doi: 10.11591/eei.v8i2.1523.

[10] K. Bhargava, R. Gupta, A. Singhal, and A. Shrinivas, "Genetic Algorithm to Optimize Solid Waste Collection," *Proceedings of the 3rd International Conference of Recent Trends in Environmental Science and Engineering (RTESE'19)*, pp. 1–8, Jun. 2019, doi: 10.11159/rtese19.110.

[11] J. Tang, Y. Liu, R. Y. K. Fung, and X. Luo, "Industrial waste recycling strategies optimization problem: Mixed integer programming model and heuristics," *Engineering Optimization*, vol. 40, no. 12, pp. 1085–1100, 2008, doi: 10.1080/03052150802294573.

[12] D. Anghinolfi, M. Paolucci, M. Robba, and A. C. Taramasso, "A dynamic optimization model for solid waste recycling," *Waste Management*, vol. 33, no. 2, pp. 287–296, Feb. 2013, doi: 10.1016/j.wasman.2012.10.006.

[13] A. H. Ali and M. M. Shakir, "Solid waste collection optimization using scine-cosine algorithm," *Periodicals of Engineering and Natural Sciences*, vol. 8, no. 1, pp. 382–389, Mar. 2020.

[14] F. Sarwar, F. Islam, M. S. Sakib, and S. Halder, "Optimizing a solid waste management model using particle swarm optimization," *Proceedings of the International Conference on Industrial Engineering and Operations Management*, pp. 1799–1806, Jul. 2019.

[15] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, and S. M. Mirjalili, "Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems," *Advances in Engineering Software*, vol. 114, pp. 163–191, Dec. 2017, doi: 10.1016/j.advengsoft.2017.07.002.

[16] U. Can and B. Alatas, "Performance comparisons of current metaheuristic algorithms on unconstrained optimization problems," *Periodicals of Engineering and Natural Sciences*, vol. 5, no. 3, pp. 328–340, 2017, doi: 10.21533/pen.v5i3.120.

[17] S. Mirjalili, "SCA: A Sine Cosine Algorithm for solving optimization problems," *Knowledge-Based Systems*, vol. 96, pp. 120–133, Mar. 2016, doi: 10.1016/j.knosys.2015.12.022.

[18] S. Mirjalili, S. M. Mirjalili, and A. Hatamlou, "Multi-Verse Optimizer: a nature-inspired algorithm for global optimization," *Neural Computing and Applications*, vol. 27, no. 2, pp. 495–513, 2016, doi: 10.1007/s00521-015-1870-7.

[19] A. Hatamlou, "Black hole: A new heuristic optimization approach for data clustering," *Information Sciences*, vol. 222, pp. 175–184, Feb. 2013, doi: 10.1016/j.ins.2012.08.023.

[20] S. Q. Salih and A. A. Alsewari, "A new algorithm for normal and large-scale optimization problems: Nomadic People Optimizer," *Neural Computing and Applications*, vol. 32, no. 14, pp. 10359–10386, Jul. 2020, doi: 10.1007/s00521-019-04575-1.

[21] M. A. Ghorbani, R. C. Deo, V. Karimi, Z. M. Yaseen, and O. Terzi, "Implementation of a hybrid MLP-FFA model for water level prediction of Lake Egirdir, Turkey," *Stochastic Environmental Research and Risk Assessment*, vol. 32, no. 6, pp. 1683–1697, 2018, doi: 10.1007/s00477-017-1474-0.

[22] A. D. Mehr, V. Nourani, E. Kahya, B. Hrnjica, A. M. A. Sattar, and Z. M. Yaseen, "Genetic programming in water resources engineering: A state-of-the-art review," *Journal of Hydrology*, vol. 566, pp. 643–667, Nov. 2018, doi: 10.1016/j.jhydrol.2018.09.043.

[23] Z. M. Yaseen *et al.*, "Prediction of evaporation in arid and semi-arid regions: a comparative study using different machine learning models," *Engineering Applications of Computational Fluid Mechanics*, vol. 14, no. 1, pp. 70-89, 2020, doi: 10.1080/19942060.2019.1680576.

[24] S. Q. Salih *et al.*, "Viability of the advanced adaptive neuro-fuzzy inference system model on reservoir evaporation process simulation: case study of Nasser Lake in Egypt," *Engineering Applications of Computational Fluid Mechanics*, vol. 13, no. 1, pp.

878–891, Jan. 2019, doi: 10.1080/19942060.2019.1647879.
[25] S. Q. Salih, A. A. Alsewari, and Z. M. Yaseen, "Pressure Vessel Design Simulation: Implementing of Multi-Swarm Particle Swarm Optimization," *ICSCA '19: Proceedings of the 2019 8th International Conference on Software and Computer Applications*, Feb. 2019, pp. 120–124, doi: 10.1145/3316615.3316643.
[26] W. Jing *et al.*, "Implementation of evolutionary computing models for reference evapotranspiration modeling: short review, assessment and possible future research directions," *Engineering Applications of Computational Fluid Mechanics*, vol. 13, no. 1, pp. 811–823, Aug. 2019, doi: 10.1080/19942060.2019.1645045.
[27] S. Q. Salih, "A New Training Method based on Black Hole Algorithm for Convolutional Neural Network," *Journal of Southwest Jiaotong University*, vol. 54, no. 3, pp. 1–1, 2019, doi: 10.35741/issn.0258-2724.54.3.22.
[28] S. Q. Salih, A. R. A. Alsewari, B. Al-Khateeb, and M. F. Zolkipli, "Novel multi-swarm approach for balancing exploration and exploitation in particle swarm optimization," *International Conference of Reliable Information and Communication Technology*, vol. 843, pp. 196–206, 2019, doi: 10.1007/978-3-319-99007-1_19.
[29] S. Q. Salih and A. A. Alsewari, "Solving large-scale problems using multi-swarm particle swarm approach," *International Journal of Engineering & Technology*, vol. 7, no. 3, pp. 1725–1729, 2018, doi: doi: 10.14419/ijet.v7i3.14742.
[30] L. P. Madin, "Aspects of jet propulsion in salps," *Canadian Journal of Zoology*, vol. 68, no. 4, pp. 765–777, Apr. 1990, doi: 10.1139/z90-111.
[31] P. A. V. Anderson and Q. Bone, "Communication between individuals in salp chains. II. Physiology," *Proceedings of the Royal Society of London. Series B. Biological Sciences*, vol. 210, no. 1181, pp. 559–574, 1980, doi: 10.1098/rspb.1980.0153.
[32] H. T. Al-Rayes, H. T. Ibrahim, W. J. Mazher, O. N. Ucan, and O. Bayat, "Feature Selection using Salp Swarm Algorithm for Real Biomedical Datasets Recent heuristic optimization algorithms in feature selection View project Feature Selection using Salp Swarm Algorithm for Real Biomedical Datasets," *IJCSNS International Journal of Computer Science and Network Security*, vol. 17, no. 12, pp. 13–20, Dec. 2017.
[33] M. A. Hannan, M. Akhtar, R. A. Begum, H. Basri, A. Hussain, and E. Scavino, "Capacitated vehicle-routing problem model for scheduled solid waste collection and route optimization using PSO algorithm," *Waste Management*, vol. 71, pp. 31–41, Jan. 2018, doi: 10.1016/j.wasman.2017.10.019.

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