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Solid waste collection optimization using scine-cosine algorithm

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ABSTRACT

In this study, a mathematical model for optimizing the cost of solid waste recycling and management was developed. Sine-Cosine Algorithm (SCA) was used during the optimization process to identify the level of disposed solid wastes and recycled solid wastes. SCA is a recent optimization algorithm, which requires several initial individual random solutions and requires their outward or inward fluctuation towards the best solution with respect to a mathematical relationship that depends on sine and cosine functions. This algorithm also integrated several adaptive and random variables to ensure the exploration and exploitation of the solution space in different optimization tasks. The outcome of this study suggested the effectiveness of the SCA for least distance path allocation while effectively considering all factors.

Keywords: Optimization, Solid Waste Collection, Scine-Cosine Algorithm, Operational Research, Optimization Algorithms

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1. Introduction

In today's world, the number of industries is increasing geometrically for accomplishing the demand of a rapidly growing population. With this growing number of industries, the total amount of production is also accelerating, and no production is possible without generating waste. Appropriate waste management is an appropriate way of making the world a comfortable habitat. Solid waste is mainly generated by human activities and its management often consists of controlling the generation, separation at source, storage, collection, transportation, processing, and disposal following public health, economic, and environmental principles[1]. Solid waste management (SWM) is primarily aimed at reducing the dangerous effects of indiscriminate solid wastes disposal on the environment. Here, this study focused on one of the most important phases of SWM, which is solid wastes collection.

The contribution of this study is to emphasize ecological concern as an unseparated part of the industrial organization. The next contribution is environmental awareness and cost minimization. With the appropriate management of waste, the cost of the production process will be significantly reduced[2]. In this study, waste recycling and disposal were considered as the two processes of SWM. The conversion of waste material into useful materials is known as the recycling process; thus, the cost of production can be optimized. The steps of SWM include waste collection from source, storing them for proper management, passing through a treatment process, recycling the suitable material, and finally disposing the rest of the waste. So, recycling and disposal are the two main processes of SWM. Waste is disposed when there is no value in the residual waste as it is no longer useful for any production process[3]–[5].

In this study, mathematical models for recycling and disposal costs were developed. The models were solved with the SCA approach which is a population-inspired heuristic developed by[6] finding the solutions to optimization problems. It is an effective and simple algorithm for optimizing real-world problems with

unknown spaces. The SCA, as the name implies, is dependent on the mathematical sine-cosine function; it uses these functions to effectively explore and exploit the solution space between two solutions in a bid to establish better solutions in the solution space.
The paper is structured as follows: Section 2 presents an overview on the optimization problems and algorithms, while Section 3 presents the formulation of solid waste management problem mathematically. Section 4 presents the mathematical model of the SCA algorithm. Finally, sections 5, 6 and 7 present the proposed algorithm, results and conclusion of the study, respectively.

2. Optimization Problems and Algorithms

In any scientific and engineering fields. There are hundreds, may be thousands of optimization problems. This type of problems when there is no known optimal solution, or there is no method or algorithm which can find the optimal solution in a deterministic time. These problems are called Non-Deteremenstic Polynomial Time (NP). Generally speaking, they could be classified into two different types of problems based on the existance of constraints, constrained and unconstrained optimization problems. The generalized mathematical formulation for these probles is given in the following equation:

$$Min/Max\ \ f_i(X) = \{i = 1,2,3 \dots D\} \quad (1)$$

S.T

$$g_k(x) \leq 0\ \ \{k = 1,2,3 \dots, K\} \quad (2)$$

$$h_j(x) = \ 0 \quad \{j = 1,2,3, \dots, J\} \quad (3)$$

Where $f_i(x)$ represents the objective function or the mathematical formulation of the optimization problem which needs to be minimized or maximized, while $g_k(x)$ and $h_j(x)$ represent the inequality and equlaticy constraints of the optimization problem. Finally, x represents an individual decision variable, or an individual vector of decision variabels. The number of decision varibles has a great impact on the problem itself, where there are two types of problems: small or normal scale problems where there are a small number of decision variables (i.e., less than 100). While the second type is called Large-scale problems where there are a huge number of decision variables (i.e., more than 100), in some cases, these problems contain thousands of decision variables making the searching process very hard.

During the past few decades, a lot of optimization algorithms have been proposed for solving such kind of problems. The majority of these algorithms were inspired from the nature. They simulate or mimic natural phenomenon, such as a living organizim (ex: movements of birds, flashing of fireflies, hunting stratigies of grey wolfs, movements of nomads in the desert)[7]. Some of the proposed algorithms were inspiring from mathematical equations, such as Scine-Cosin Algorithm (SCA) which is used in this research for solving the optimization problem of Solid Waste Collection. Moreover, there are another type of algorithms were inspired from some physical phenomenon, such as the Black Hole (BH) algorithm which mimcs the black hole in the universe, Multiverse Optimization Algorithm (MVO) which simulates the theory of multi-universces, or simulating the movement of the nomad people in the desert for finding better positions near to the water sources[6], [8]–[10]. The success of metaheuristics attracted the researchers from different filds for utilizing them in their optization problems. In the field of Machine Learning, researchers have applied different metahueristics for enhancing their prediction models in different case studies[11]–[15]. Moreover, engineering problems have been solved using this type of algorithm[16], [17]. The researchers also tried to solve the Feature selection problem, which is a popular optimization problem in data science, using metaheuristics[18], [19]. More applications can be found in the letriture when metaheuristics were utilized for solving different case studies[20]–[29].

Two main components in any population based – multi solution optimization algorithm – effect on the searching process of the algorithms. These components are exploration – or global search ability – and explotation – or local search ability. These two compont should be balanced based on the targeted optimization problem, as the increasing in one searching ability over the over will lead to slow searching process, or may lead the algorithm to be trapped in local optima[30], [31].

In the next section, the solid waste collection problem is explained in details, and formulated mathematically as an optimization problem.

3. Problem Formulation

For a green supply chain, companies need to minimize waste generation and the only way to waste minimization is to manage waste appropriately. For this reason, this study considers the management process for solid waste. Among them, recycling and disposing solid waste in industries are considered. The goal is to identify different criteria for waste management and using this to formulate a mathematical model. Finally, all the models were combined to formulate an objective function for cost minimization. For model formulation in this study, some criteria were assumed to convenience the process. They are Independent demand rate of items, Demand rate is constant in each period, and no volume discounts.
The objective function is simply defined as follows:

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

Where:
D_i = demand for each product per period,
Cr_i = recycle cost of each product,
Cd_i = disposal cost of each product,
Ud = upper bound of disposing per period,
Ur = upper bound of recycling per period,
Lr_i = level of recycling per period,
Ld_i = level of solid dispose per period,
W_t = total amount of solid waste per period,
and $i = \{1,2,\dots,n\}$, where n is the number of items.
α and β are:

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

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

Two main constraints should be taken into consideration:

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

4. Scine-Cosine Algorithm (SCA)

SCA was recently proposed by [6] as a population-inspired heuristic in which multiple random solutions are first created before being made to revolve either towards or outwards the best solution. Additionally, the exploration and exploitation of the solution space are ensured by emphasizing that various adaptive and random variables are incorporated in the SCA. In any stochastic population-based optimization process, the two major phases of the process are exploration and exploitation; regarding SCA, the following equations introduced the exploration and exploitation processes into the algorithm:

$$X_i^{t+1} = \begin{cases} x_i^t + r_1.\sin(r_2).\left|r_3 . P_i^t - x_i^t\right|, r_4 < 0.5 \\ x_i^t + r_1.\cos(r_2).\left|r_3 . P_i^t - x_i^t\right|, r_4 \geq 0.5 \end{cases} \tag{7}$$

where x_i^t represents the current position of a solution in i_{th} dimension at t_{th} iteration, P_i^t represents the position of the destination in i_{th} dimension at t_{th} iteration and the absolute value is represented by $|.|$. Furthermore, r_1 expresses the range of the next position (ranging between [-2, 2] in this study), r_2 expresses the range of the expected movement of the solution towards or outwards the destination (ranging from [0, 2p]), r_3 expresses the destination of the random weight that has a stochastic influence, covering (r_3 >1) or reducing (r_3 <1) the distance, r_4 expresses the equal swapping from sine-cosine or cosine-sine (ranging from [0, 1]).

Sine and cosine functions' effects on Eq. 7 in the next position Equation (7), determines the space between two solutions in the solution space. The solutions can change the amplitude of sine-cosine functions in order to search outside the space between their respective destinations; this ensures the efficient exploration of the solution space. However, space among two solutions can be exploited by leveraging the periodic pattern of sine-cosine functions; this can be done by shifting a solution close to another solution. Sine-cosine functions' effects in the range of [-2, 2].

The following equation is used to adaptively change the amplitude of sine-cosine functions in Eq. 3 to ensure a balanced exploration and exploitation phases in SCA:

$$r_1 = a - t\frac{a}{MIT} \tag{8}$$

where *t* represents the current iteration and MIT represent the overall number of iterations (equal to 100); a is a constant set to the value of 2 in this study. r_1 decreases linearly in Eq. 8 from a to 0.

Scine-Cosine Algorithm

Input: $\mathbf{No. of\ Agents}$ ($\boldsymbol{NX}$), No. of $\mathbf{Iterations}$ (**MIT**),
1. Initialize all ***Agents (X)*** in the Population
2. Evaluate the fitness of each Agent
3. $\boldsymbol{r_1}$ **= Random (0,1)**
4. ***Do While*** ($\boldsymbol{t} \leq \mathbf{MIT}$)
5. ***For*** *each* ***Agent*** ($\boldsymbol{X_i}$) *in* the Population
6. Determine the best solution founded in the past iterations
7. $\boldsymbol{r_1}$ **= update via eq. (8)**
8. $\boldsymbol{r_2}$ **= Random (0,1)**
9. $\boldsymbol{r_3}$ **= Random (0,1)**
10. $\boldsymbol{r_4}$ **= Random (0,1)**
11. Move the Agent ($\boldsymbol{X_i}$) to the next position via eq. (7)
12. Evaluate the new solutions
13. ***End For***
14. t = t + 1
15. ***Loop***
16. *Return the best solution founded after all iterations*

Figure1. The pseudocode of SCA

5. The Proposed Algorithm

As stated previously, the main contribution of this paper is to implement Scine-Cosine Algorithm (SCA) for optimizing and solving the problem of solid waste collection. The proposed algorithm consists of several main steps. Started by initilizaing the all agents in the search space using a uniform distribution equation, as follows:

$$X_i = LowerBound + (Rand * (UpperBound - LowerBound)) \tag{9}$$

Where X_i represents the searching agent, while *LowerBound* and *UpperBound* represent the lower and lower boundaries of the search space respectively. *Rand* is a random number in range [0,1]. Eq (9) above distributes the searching agents – or generates the solutions – in the search space randomly.

Generally, the size of each agent or solution depends mainly on the dimension of the optimization problems. In this research, the size of each solution is 8, as presented in eq.4 (See Section 3). The type of these decion variables is continuous or real values.
Each solution should be evaluated, and the fitness value is calculated using eq (4). As the aim the research to minimize the solid waste, then, the solution with lower fitness value is better. Thus, the solution with lowes as compared to all other agents is selected and kept as the best solution so far.
After all agents are initialized and evaluated, they move to better position via eq. (7). Then, all random variables ($r_1, r_2, r_3,$ and r_4) are updated. The solution are re-evaluated using eq (4) in order to find a new best solution. These steps are executed for many times until the stop condition is satisfied, which is the number of iterations in this study. Figure 2 below illustrates the main flow chart for the proposed algorithm.

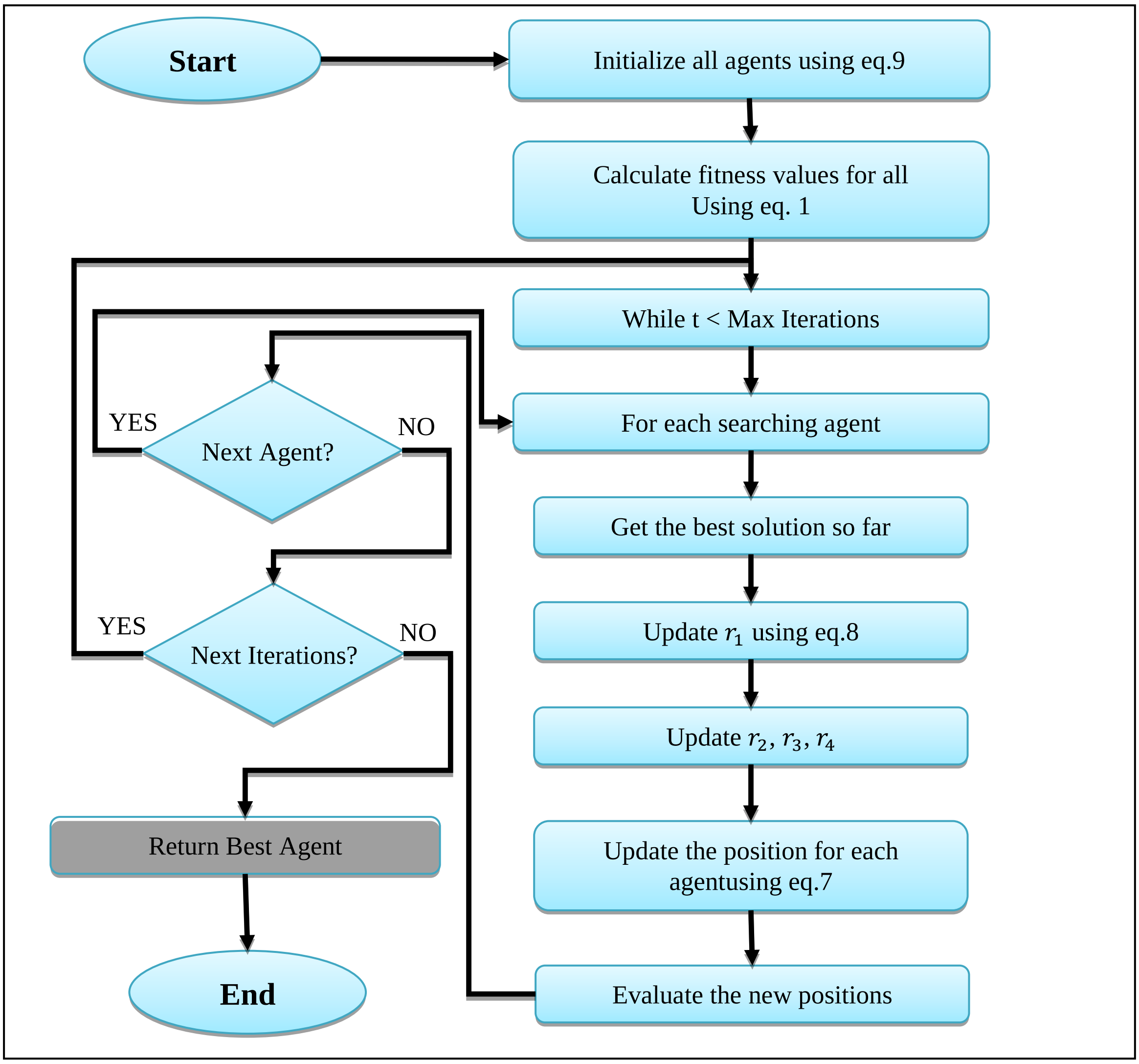

Figure 2. The flowchart of sca for solid waste collection problem

6. Results and Discussion

Both of the main mathematical modeling for the solid waste optimization problem with the proposed algorithm are designed and evaluated using MATLAB probramming language version 2017b. The propoposed SCA algorithm has been evaluated using several population sizes (10, 20, 30, 40, and 50). For comparison purposes, Particle swarm optimization (PSO) algorithm has been also implemented using the same conditions where ($c_1 = 1.42, c_2 = 1.42$) for the same optimization problem.
The obtained results are presented in Figure 3, which illustrates the performance of SCA when utilized for solving the solid waste collection problem based on different number of search agents. It is clear that the SCA is better in terms of the stability of the algorithm, in other words, the standard deviation of the algorithm for

SCA is lower than the standard deviation of PSO (Std. for SCA = 0.0842, Std. for PSO = 1.0541). Meaning that, the algorithm reached almost the same solution for each run, while PSO was varied more than SCA.

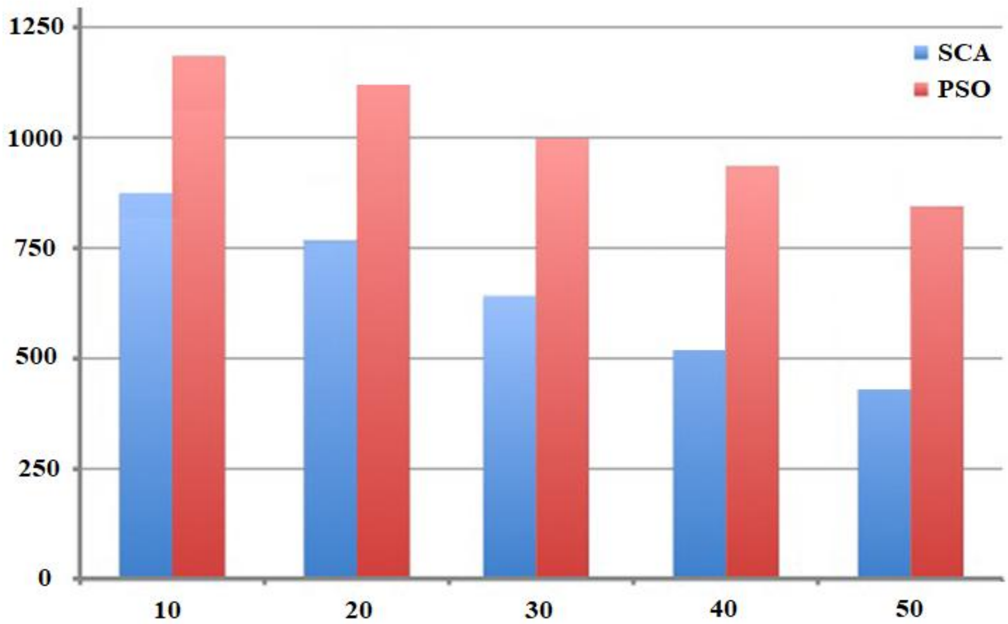

Figure 3. The best results obtained using SCA and PSO for all sizes of search agents

It is clear that the number of the searching agents affect on the searching performance of the algorithm. As the number of the searching agents increased, the possibility for finding better positions is increased as well. It can be noted that PSO also get increased when the number of the particls increased, however, the enhancement rates where smaller than SCA. IT is worth to mention that the worst case of SCA is better than the best case of PSO, which proved that the main contribution of this paper has been achieved.

Moreover, both algorithms have been compared using their convergence analysis. The convergence for both algorithms is presented if Figure 5, it is obvious than SCA has better convergence than PSO due to the well belancing between the global and local search abilities. However, the balancing mechanism in PSO is affected mainly by the value of the parameters c_1 and c_2.

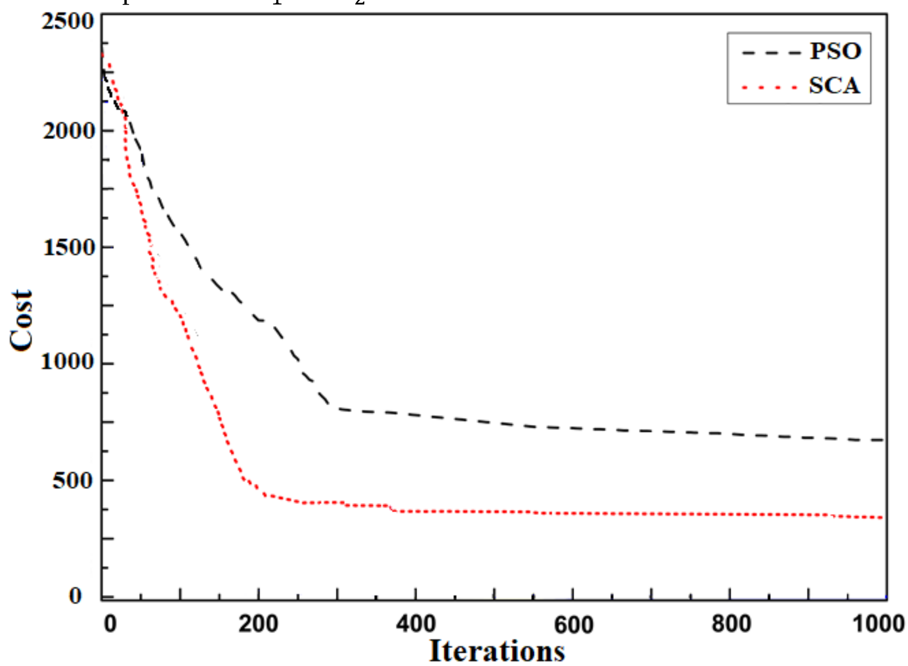

Figure 4. A comparasion based on the convergence analysis (Searrch Agents = 50)

From Figure 4 above, SCA was faster than PSO at the beginning for the first 200 iterations, then, the enhancement in the performance of the algorithm was slow. However, there was an enhancement in the performance until the last iteration (i.e, 1000). This performance proved that SCA was able to discover better positions and it did not fall in the local minima when it was searching for the best solution.

7. Conclusion

Optimization problems is a type of problems when there is no linear method has the ability to handle them. Solid waste collection problem is one of this type of problems, which needs to be handled and solved by a specific type of algorithms, which called “Metaheuristics”. In this study, Scine-Cosine Algorithm (SCA) which is a metaheuristic developed recently is used for solving Solid waste collection problem. The results showed that the proposed algorithm has found better solutions than the well-known algorithm “Particle Swarm Optimization (PSO)”. Also, the proposed algorithm has converged faster than PSO when the same number of iterations used for solving the same problem. For future studies, the proposed algorithm could be used for handling the same problem with dynamic data, where the sensors used for collecting the data from the environment.

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