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Optimization of gas cyclone design using evolutionary computing approach

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Abstract

The concept of Evolutionary Computing method covers the process of searching for an optimal solution inspired by natural evolution. It can also be viewed as a family of trial and error problem solvers which can be considered as global optimization methods with a metaheuristic or stochastic optimization concept, characterized by the use of a population of candidate solutions. Such methods include Genetic Algorithm, Particle Swarm Intelligence and Differential Evolution among others. The conventional approach adopted in the design process is to use mathematical models and sensitivity approach to obtain relevant optimal design parameters. Accurate computation and optimization of the design parameters of new equipment is one of the main concerns of design engineers. The goal here is to apply evolutionary computing methods to design a gas cyclone with optimum design parameters taking into cognisance that the optimization process is complicated which requires an extensive search of a very large input space. The motivation of this research effort is the avoidance of complex mathematical models and sensitivity approach for gas cyclone design. The result shows that a hybrid Differential Evolution based Particle Swarm Optimization outperformed standard Genetic Algorithm, Particle Swarm Intelligence and Differential Evolution.

Keywords: Evolutionary Computing; Genetic Algorithm; Particle Swarm Optimization; Differential: Gas Cyclone; Cyclone efficiency

1. Introduction

Evolutionary Computing is the application of computer system to an optimization problem based on the principles of natural selection for reproduction or to simulate/mimic the natural evolution andevolutionary genetic operators such as selection, crossover and mutation. This search and optimization method which is based on evolutionary principles is also known as Evolutionary Computing. This concept usually starts its search operations with a random set of solutions which may be coded in binary string. With a well stated objective function, each solution is assigned a fitness function. After selection of the fittest, the population of solution is modified to a new population by applying those three genetic operators. The iterative process continues by applying the operators in each generation until the criterion for termination is attained [1,2,3,4]. In the domain of gas cyclone design, there are many design parameters that are difficult to be obtained purely by traditional mathematical modelling approaches due to many uncertainties as well as numerous simplifications and assumptions. This design is usually based on the application of mathematical models derived to simulate the operation of such equipment and in some instances are subjected to subjective judgments of the design engineer. Designs have to be optimized in order to maximize performance and attain most economic results. As the dimension of equipment increases, there could be corresponding increase in performance. However, a point is reached when further increase result in low performance and uneconomical results. Therefore, identifying an optimal dimension that produce the best performance is the main interest in design problems. The goal here is to apply evolutionary

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computing methods to design a gas cyclone with optimum design parameters taking into cognisance that the optimization process is complicated which requires an extensive search of a very large input space.

2. Material and Method

2.1. Genetic Algorithm (Ga)

The evolutionary computing is a popular optimization technique that is based on the ideas of natural evolution. The result is improved upon by iteratively finding solution to an optimization problem. In general, the process of GA consists of the following steps: First of all, an initial population is randomly generated and each solution known as chromosomes is usually expressed in the form of a binary string. From the generation of initial population, a new population is formed using the fittest chromosomes based on the objective function. Each solution is called a chromosome and it is usually in the form of a binary string. After the generation of the initial population, a new population is formed that consists of the fittest chromosomes as well as offspring of these chromosomes based. The value of the fitness for each chromosome is determined from a user-defined objective function. In Genetic Algorithm/Evolutionary Computing, offspring are generated by applying genetic operators such as selection, crossover and mutation which are the most fundamental. The selection operator determines which chromosome will survive. Having selected a pair of chromosomes for crossover, one or more randomly selected positions are exchanged. The newly crossed over chromosomes are then combined with the rest of the chromosomes to produce a new generation. Usually, the mutation operation follows the crossover operation and it entails arbitrary selection of selected bits in a chromosome for inversion using a very small mutation rate [2,3,4,5].

2.2. Overview of Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is an evolutionary computation technique, first introduced by Kennedy and Eberhart [6,7], The main idea is used to model a group social behavior such as the way birds travel when trying to find sources of food, or fish schooling. In PSO, the behavior is modeled in such way is that the "particles" inside the "swarm" (or population) are treated as solutions to a given problem with exchange of information. And as such, each particle will adjust its movement towards its own previous best position and global best previous position. The flowchart of the method is given in Fig. 1 c1 and c2 are two positive constants, called the cognitive and social parameter respectively; ri1 and ri2 are random numbers uniformly distributed within the range [0, 1]. In each iteration, Eq. (1) is used to determine the i-the particle's new velocity, while Eq. (2) provides the new position of the i-th particle by adding its new velocity, to its current position. The performance of each particle is measured according to a fitness function, which depends on the problem. The role of the inertia weight w is considered important for the PSO's convergence behavior. The inertia weight is employed to control the impact of the previous history of velocities on the current velocity. Thus, the parameter w regulates the trade-off between the global (wide-ranging) and the local (nearby) exploration abilities of the swarm. A large inertia weight facilitates exploration (searching new areas), while a small one tends to facilitate exploitation, i.e. fine-tuning the current search area. A proper value for the inertia weight w provides balance between the global and local exploration ability of the swarm, and, thus results in better solutions. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. After finding the two best values, the particle updates its velocity and positions with following equations (1) and (2).

$$V[n+1] = v[n] + c1 * rand() * (pbest[n] - X[n]) + c2 * rand()*(gbest[n]-X[n]) \quad (1)$$
$$X[n+1] = X[n] + v[n+1] \quad (2)$$

V[n] is the particle velocity, X[n] is the current particle (solution). pbest[n] and gbest[n] are defined as stated before. Rand () is a random number between (0, 1). c1, c2 are learning factors and sually c1 = c2 = 2.

The procedure describing proposed PSO approach is as follows.

Initializing PSO with population size, inertia weight and generations.

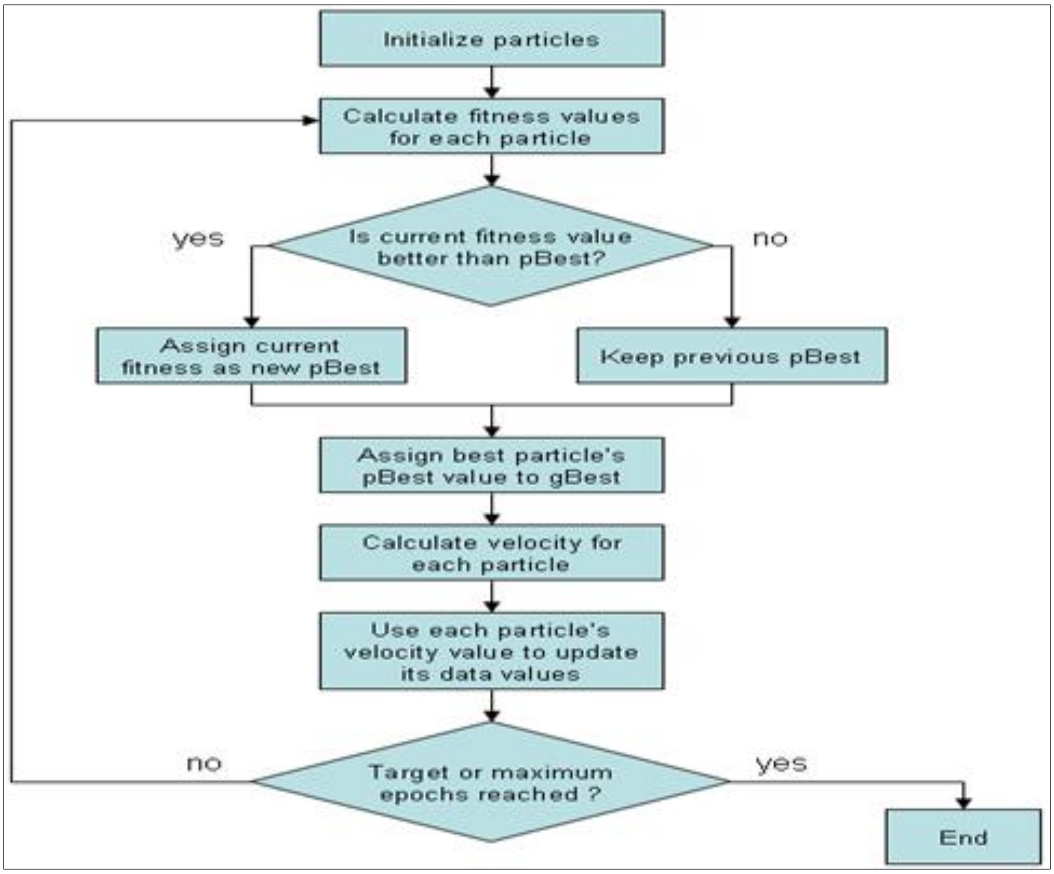

Figure 1 Flow diagram illustrating the particle swarm

- Evaluating the fitness of each particle.
- Comparing the fitness values and determines the local best and global best particle.
- Updating the velocity and position of each particle till value of the fitness function converges

2.3. Differential Evolution (DE)

Differential Evolution, like other evolutionary computation methods, starts with an initial population that is generally randomly initialized. After determining the population, a new candidate individual is generated by applying mutation and crossover operators [8,9, 10]. The mutation operator creates mutant candidate by perturbing a randomly selected candidate with the difference of two other randomly selected candidates. This candidate then becomes the input of selection operator and is examined if the candidate is better than the current member. If it is better, it will enter the next generation otherwise the current member remains in the population.

2.4. Hybrid Differential Evolution with Particle Swarm Optimization Algorithm (DEPSO)

The proposed DE-PSO as mentioned earlier is a hybrid version of DE and PSO. DE-PSO starts like the usual DE algorithm up to the point where the trial vector is generated. If the trial vector satisfies specified conditions, then it is included in the population otherwise the algorithm enters the PSO phase and generates a new candidate solution. The method is repeated iteratively till the optimum value is reached. The inclusion of PSO phase creates a perturbation in the population, which in turn helps in maintaining diversity of the population and producing a good optimal solution [11,12,13,14].

3. The Gas Cyclone Design

Cyclones are devices used for sizing, classification and screening of particulate materials in mixture with fluid (gases or liquid). Cyclones come in many sizes and shapes and have no moving parts. The mode of operation involves the process of subjecting the flowing fluid to swirl around the cylindrical part of the device. They impact the cyclone walls, fall down the cyclone wall (by gravity) and are collected in a hopper. The most important parameter of a cyclone is its collection efficiency and the pressure drop across the unit [15, 16, 17,18]. Cyclone efficiency is increased through:

- Reduction of cyclone diameter, gas outlet diameter and cone angle;
- Increasing the cyclone body length.

Capacity is however increased by increasing the cyclone diameter, inlet diameter and body length. Increasing the pressure drop give rise to:

- Increase in separation efficiency
- Higher capacity
- Decrease in the underflow to throughput ratio
- Cleaner overflow

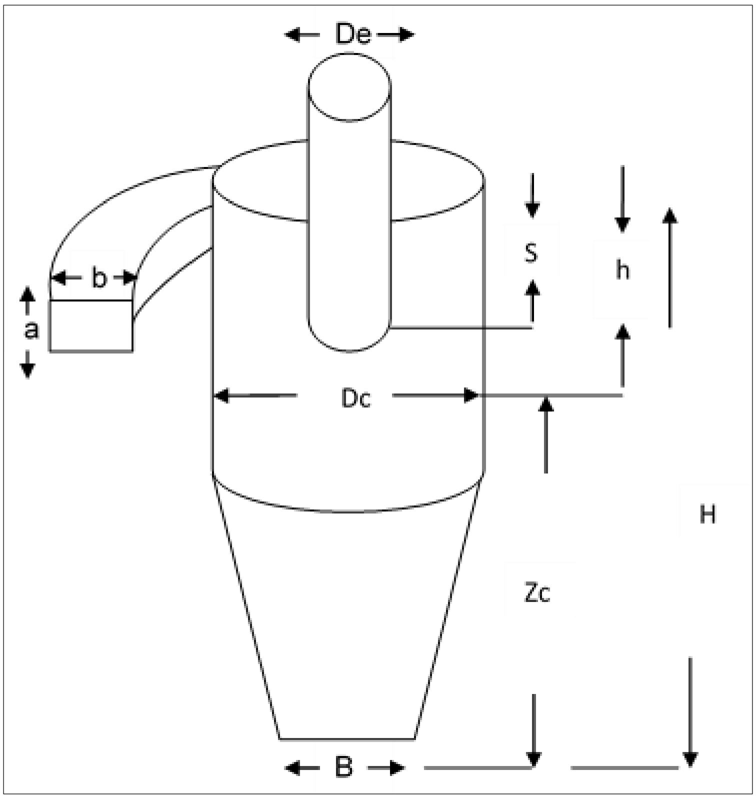

Figure 2 Gas Cyclone Geometry

The design parameters include:

- Feed rate Q m^3/s
- Cyclone diameter D_c , m
- Set cut size d_{pc} , µm
- Cyclone efficiency
- Cyclone pressure Drop D_P
- Cyclone Geometry (Dc, De(vortex finder diameter), h(cylindrical height), H(overall Height), a(Inlet height), b(Inlet width), B(cone diameter),S(vortex finder height))
- Temperature ^oC
- Pressure, N/m^2
- Viscosity, Ns/m^2
- Density fluid, kg/m^3
- Mass Median Diameter MMD, (µm)

- Geometric Standard Deviation GSD, µm
- Number of Cyclones
- Fluid density, Kg/m^3
- Particle density, Kg/m^3

Give the cyclone geometry (as shown in Fig 2.) and the operating conditions (Operating temperature, particle density), there are 5 design parameters that can be specified for a design.

- These parameters are:
- Feed Rate, Q
- Cyclone Diameter, Dc
- Set cut size dpc
- Cyclone Efficiency
- Cyclone pressure drop DP

The prediction of the performance of the cyclone separators is a challenging problem for the designers owing to the complexity of internal aerodynamic process and dust particles. Hence, modern numerical simulations are needed to solve this problem. Fluid flows have long been mathematically described by a set of nonlinear, partial differential equations, namely the Navier-Stokes equations.

3.1. Particle Cut-off Size dpc

According to Wang et al. [18,19,20], cyclone performance depends on the geometry and operating parameters of the cyclone, as well as the particle size distribution of the entrained particulate matter. Several mathematical models have been developed to predict cyclone performance. Lapple [21] developed a semi-empirical relationship to predict the cut point of cyclones designed according to the Classical Cyclone Design method, where cyclone cut point is defined as the particle diameter corresponding to a 50% collection efficiency. Wang et al showed that Lapple’s approach did not discuss the effects of particle size distribution on cyclone performance. The Lapple model was based on the terminal velocity of particles in a cyclone. From the theoretical analysis, equation (1) was derived to determine the smallest particle that will be collected by a cyclone if it enters at the inside edge of the inlet duct:

$$d_p = \sqrt{\frac{9\mu b}{2\pi NeVi(\rho p - \rho g)}} \ldots\ldots\ldots\ldots\ldots\ldots(1)$$

where: dp = diameter of the smallest particle that will be collected by the cyclone if it enters on the inside edge of the inlet duct (µm),

µ = gas viscosity (kg/m-s),
b = width of inlet duct (m),
Ne = number of turns of the air stream in the cyclone,
V_i = gas inlet velocity (m/s),
ρ_p = particle density (kg/m^3), and
ρ_g = gas density (kg/m^3).

3.2. Efficiency Calculation

The most important parameters in cyclone operation are pressure drop and collection efficiency. The pressure drop is given by the difference between the static pressure at the cyclone entry and the exit tube.

The fractional efficiency for J^{th} particle size, according to Lapple [21] is given as

$$\eta_j = \frac{1}{1 + \sqrt{\frac{dpc}{dpj}}} \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

d_{pc} = diameter of the smallest particle that will be collected by the cyclone

d_{pi} = diameter of the jth particle.

The overall collection efficiency of the cyclone is a weighted average of the collection efficiencies for the various size ranges, namely

$$\eta = \frac{\sum \eta j m j}{m} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where η = overall collection efficiency

η_j= fractional efficiency for J^{th} particle size

m = total mass of particle mj = mass of particle in the J^{th} particle size range

3.3. Pressure Drop Calculation

The energy consumed in a cyclone is most frequently expressed as the pressure drop across the cyclone. This pressure drop is the difference between the gas static pressure measured at the inlet and outlet of the cyclone. Many models have been developed to determine this pressure drop [22,23,24]. Some of the commonly used equations to calculate the pressure drop are;

- Koch and Licht Pressure Drop Equation

Koch and Licht (1977) expressed the cyclone pressure drop

$$\Delta P = 0.003 \rho_g V_i^2 N_{II} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

where

ρ_g = gas density (lbm/7t³)

Vi = inlet velocity (7t/s)

N_{II} = number of velocity heads (inches of water) and is expressed as

$$N_{II} = K\left(\frac{a.b}{De^2}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

K = 16 for no inlet vane

7.5 with neutral inlet vane

a,b =inlet height and width respectively

- Ogawa Equation

Another pressure drop equation takes the form of

$$\Delta P = 1/2 \rho_g V_i N_{II} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Using statistical analysis, N_{II} is expressed as

$$N_{II} = 11.3\left(\frac{ab}{Di}\right)^3 + 3.33 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

3.4. Objective Function

In this paper, the cost of operating the cyclone used instead of using two conflicting objective functions (efficiency and pressure drop). In general, the total cost per unit will a function of fixed cost cyclone and energy cost of operating the cyclone as follows[16]:

C_t=Fixed cost +energy cost

Assuming the cost of cyclone depends on its diameter, the fixed cost can be expressed as

$C_{fixed}=fN_eDc^2/YH$

Where f is an investment factor to allow for installation, H is the time worked per year, Y is the number of years.

The energy cost is given by

$C_{energy}=Q\Delta PC_e$

Where Q is the feed rate (m^3/s), ΔP is the pressure drop (Pa), C_e is cost per unit energy.

Hence, $C_t=fNe\beta_1/YH + \rho_f\varepsilon Q^3\ \beta_2/2a_o^2\ b_o^2N^2$ (8)

where$\beta_1=[d_{pc}^2(\rho_s-\rho_f)\pi N_tN_eQ/9a_ob_o^2\ \mu N]^{2/3}$

$\beta_2=[d_{pc}^2(\rho_s-\rho_f)\pi N_tQ/9a_ob_o^2\ \mu N]^{-4/3}$

The objective function is of minimization type and the EC methods search for an optimized cyclone geometry with low cost per unit.

3.5. Recommended range of operation

Among the most important characteristics of gas cyclones is the effect of pressure drop (or flowrate) on their efficiency. A properly designed and operated cyclone is expected to operate at pressure drops within a recommended range, and therefore for most cyclone designs operated at ambient conditions it is between 2 and 6 inches of water gauge (WG) (approximately from 500 to 1500 Pa). Within this range, there is increase in recovery with applied static pressure drop. At pressure drops below the bottom limit, the cyclone behaves more or less like a settling chamber, giving low efficiency due to low velocities within it which may not be enough to generate a stable vortex. Above the top limit (the value which depends very much on the cyclone design and can be as high as 15"WG i.e. 3740 Pa, depending particularly on what happens at and below the dust outlet orifice), the mass recovery does not increase with corresponding increase in pressure drop and it may actually decline; it is therefore wasteful to operate cyclones above this limit [24].

4. Gas Cyclone Design Optimization

A cyclone is required to remove carbon dust particle from affluent air coming from a thermal power station at a rate of $5.0m^3/s$ at 65^oC. The dust particles are assumed to have normal size distribution with MMD of 20µm and GSD of 1.5µm. For energy cost consideration the pressure drop in the cyclone is required to be not more than 1000 N/m^2. The density of the dust particle is $2250kg/m^3$ and cyclone operating at atmospheric pressure. What is the required geometry/size and cut size of the cyclone that you will recommend, if it is intended to attain overall efficiency of 70% and above? Q = $5m^3/s$, Temp = 65^oC, MMD = 20µm GSD 15µm, Pressure 1000 N/m^2 ρ dust particle $2250kg/m^2$

This study develops a GA, PSO, DE and DEPSO models for Gas Cyclone Design optimization and compare with Shephard & Lapple medium efficiency model. The process of proposed models in the first stage, initial design parameters of the equipment are identified. In the next stage, the fitness of each solution is determined. At the present study, we show the application of GA, PSO, DE and DEPSO methods for design optimization of the $5.0m^3/s$ Gas Cyclone equipment.

5. Results and Discussion

Figure 3 and Table3 show the Performance comparison of DEPSO with GA, DE and PSO for fitness function in eqn (8) for 1000 generations. As it can be seen DEPSO outperform DE, PSO and GA.

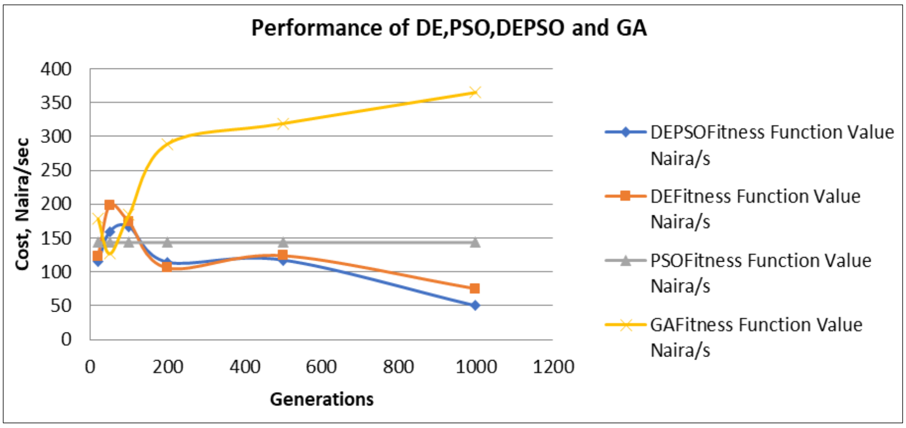

Figure 3 Performance of DE, DEPSO, PSO and GA Algorithms

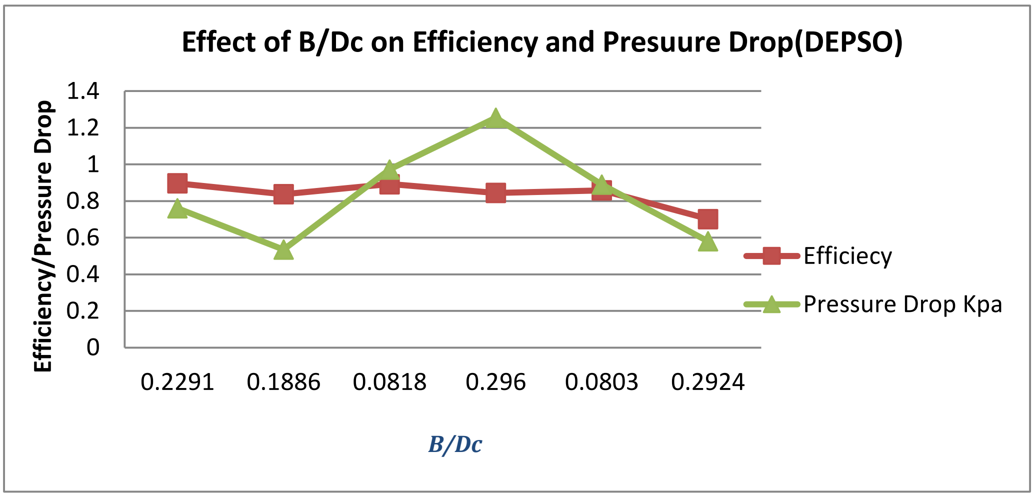

Figure 4 Effect of Dimensionless Cone Diameter (B/Dc) on Efficiency and Pressure Drop (Hybrid DEPSO) Algorithm

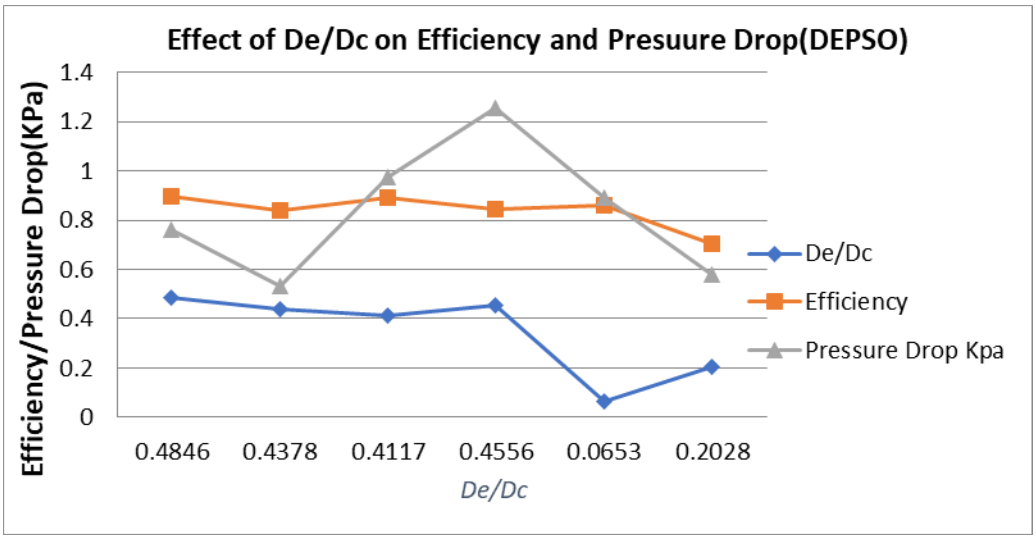

Figure 5 Effect of Dimensionless Vortex finder Diameter (De/Dc) on Efficiency and Pressure Drop (Hybrid DEPSO) Algorithm

As it can be seen in Fig. 4, by decreasing the cone diameter ratio (B/Dc), due to the increase of the tangential velocity in conical part, the collection efficiency of the particles increases and also pressure drop decreases, this behavior shows that the optimum B/Dc, (in case of DEPSO), when efficiency remains almost constant but pressure drop decreases is at B/Dc=0.1886.

Table 1 GA Parameters Used for Design Parameter Optimization

GA parameter	Value
Maximum Generation	50
Population Size	100
Crossover Rate	0.8
Mutation Rate	0.05

Table 2 DE, DEPSO Parameters Used for Design Parameter Optimization

Parameters	Value
Maximum Generation	50
Particle Size	100
Probability of crossover range, CR	0.5
Scaling Factor	1.0
w	0.729
C1	1.49445
C2	1.49445

The Optimized Cyclone Geometry (Using Genetic Algorithm, PSO DE and hybrid DE-PSO Methods) is as shown below: Cyclone Diameter, Dc: 2.078 m

Table 3 Design Parameters Are In The Ratio Of Dc

Design Parameters are in the ratio of Dc	GA	PSO	DE	Hybrid DE-PSO	Shephard & Lapple Model
Overall Cyclone height,	2.4020	3.4532	3.3065	3.6900	4.0
Inlet height, ao	0.0945	0.4908	0.4839	0.4883	0.5
Gas outlet Diameter,Deo	0.1236	0.1681	0.3814	0.1188	0.25
Cylindrical height of Cyclone,ho	1.7671	1.4302	1.9821	2.0552	2.0
Inlet width, bo	1.1990	0.2053	0.1634	0.2052	0.25
Gas Outlet Length, So	0.4539	0.4921	0.5921	0.5912	0.625
Dust Outlet Diameter,Bo	0.2651	0.3200	0.2508	0.2784	0.25
Pressure Drop (Pa)	402.22	504.50	809.06	510.23	500
Inlet Velocity m/s	10.22	11.49	14.65	11.56	19.145
Cut size dp_c(μm)	13.8	15.86	11.28	17.99	10.03
Cost/second(Naira)	417.15	9.4909	15.00	6.74	n/a

Overall Efficiency	0.8057	0.757	0.8602	0.7077	0.8976

Fig. 5 illustrates the alterations of the dimensionless diameter of the vortex finder (De/Dc) and its effects on pressure drop. It shows that, by increasing the vortex finder diameter, there is an easy fluid flow into the vortex finder, resulting to the decrease in the pressure drop of the cyclone. However, the resulting effect will lead to departure of more particles with fluid from the vortex finder and reduce the efficiency. Hence, the optimum dimensionless (De/Dc) is 0.4378.

6. Conclusion

This research effort was aimed at using an Evolutionary Computing (EC) approach for Gas Cyclone design and attempted to determine the optimum value of design parameters to attain maximum economic results. In this paper, it can be concluded that:

- In the cyclone example illustrated, we showed a hybrid of DE and PSO called DE-PSO was proposed and outperformed the classical GA, DE and PSO.
- From Fig4, it was observed that with efficiency almost constant, the optimum point is where the pressure drop is the least.
- Increasing the diameter of vortex finder will decrease of the pressure drop so also is the efficiency. Hence, the designer needs to be aware of making an informed decision regarding the combined effects of the desired efficiency and pressure drop in the cyclone system.

This concept of Evolutionary Computing can also be applied to other optimization problems in Engineering.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest.

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