# DIFFERENTIAL EVOLUTION ALGORITHM WITH PARAMETER ADAPTATION STRATEGY FOR OPTIMAL DESIGN OF HYBRID RENEWABLE ENERGY SYSTEM

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***Abstract:*** *In this paper, a simple, efficient and most powerful differential evolution (DE) algorithm with parameter adaptation strategy (DE-PAS) is proposed and implemented for an optimal design of hybrid renewable energy system (HRES). The performance and efficiency of a simple differential evolution (DE) algorithm is extensively influenced by the proper choice of parameters and adaptive strategies; therefore, a differential evolution algorithm with parameter adaptation strategy (DE-PAS) is proposed in this paper to enhance the performance of existing simple DE algorithm. In DE-PAS, the suitable control parameters can be achieved in different evolution stages. Best suitable self-adaptation (SA) techniques for mutation rate F and crossover rate CR were studied using the chosen HRES problem. The computational results show that the fitness based adaptation technique for F and SA technique for CR performs better than the other adaptation techniques. To demonstrate the efficiency and reliability of the proposed DE-PAS algorithm is compared with different state-of-the-art evolutionary algorithms. Comparison with the best-known algorithm reflects the superiority of proposed algorithm in terms of accuracy, convergence speed and computational time for the chosen HRES problem.*

***Keywords:*** *Hybrid renewable energy system (HRES), Differential evolution with parameter adaptation strategy (DE - PAS), mutation rate, crossover rate, fitness based adaptation, self-adaptation (SA).*

## 1. Introduction

Renewable energy sources offer clean and economically competitive alternatives which reduces the dependency on conventional power generation. But the periodic nature of these sources is the main barricade for their rapid implementation and has motivated the researchers in incorporating one or more renewable energy source into a single system [1][2]. A hybrid renewable energy system (HRES) integrates different renewable energy sources.

Depending upon the geographical location and energy demand of a given area an optimal combination of different renewable energy source will be used in an appropriate and cost-effective manner. The so formed HRES is more reliable as it eliminates the disadvantages of individual renewable energy sources and can be used for the development of rural area [2].

Commercially available HRES include solar photovoltaic (solar PV)-diesel, solar PV-battery, wind-battery, wind-diesel, solar PV-wind-battery and solar PV-wind-diesel battery systems [2]. In this paper, solar PV, wind, micro-hydro, diesel generators and batteries are incorporated in HRES. The optimal design of HRES makes them cost effective, reliable and environmental friendly system which supplies the load economically. The optimal design of non-linear HRES is essential for the economic performance of the system on the long run. Classical optimization techniques can be used for optimizing these HRES problem.

Though the conventional methods have advantages like few control parameters and less computational time, it fails to reach global optima for the problems with large dimensional and discrete search space [3][4]. Various evolutionary optimization techniques are used by researchers across the world to optimize the design of HRES [5] [6]. Differential evolution algorithm is one of the most powerful, direct, reliable, stochastic, versatile population based heuristic real parameter optimization technique and demonstrated good performance in solving many real time engineering problems. Similar to other evolutionary methods, DE has its own disadvantages: computationally expensive, too time consuming in finding global optimum or good suboptimal solution. Therefore, an improvement in DE algorithm with the aim of faster convergence rate, good quality solution and to handle discrete variables [7][8][9]. Similar to other EAs, the performance (searching accuracy and convergence speed) of DE algorithm is sensitive to the choice of parameters like population size $N$, mutation rate or scale factor $F$ and crossover rate or constant $CR$ [8]. Proper choice of these parameters is necessary as the objective function of a system is sensitive to them [10]. In [11] -[15] different techniques in finding an optimal set of control parameters is described. In recent trends, the self adaptive strategies as in [3][11][12] are used in the optimization algorithm to tune their parameters.

In this paper, to enhance the operation of DE two modifications are implemented to give a so-called the differential evolution with parameter adaptation strategy (DE-PAS) algorithm. Firstly, an adaptation technique based on the fitness value of the problem is used for the mutation rate $F$. Secondly, a self adaptation technique is used for the crossover rate $CR$. The details description of these improvements is presented in the following sections. The robustness, efficiency and performance of DE-PAS is verified through chosen HRES problem. Numerical results show that the proposed DE-PAS algorithm is more efficient than the other state-of-the-art algorithms for the chosen HRES problem.

The rest of the paper is organized as follows: Section 2 and section 3 describes the selected HRES and its problem formulation respectively. General description of stages present in DE - PAS algorithm is explained in section 4. Section 5 is allotted for choosing the optimal population size, suitable adaptation technique for $F$ and $CR$ for the selected problem by performing a comparison over different conditions. The comparison of the proposed DE - PAS algorithm with the other variants of DE is discussed in section 6 as results and discussion. Finally conclusion is drawn in section 7.

## 2. Hybrid renewable energy system (HRES)

A HRES generally comprises of two or more renewable energy sources combined with a conventional energy sources and a storage system as a backup system [16][17]. In HRES, the renewable energy sources acts as the primary energy sources and conventional energy sources acts as the secondary energy sources[18] .In this paper, the stand-alone HRES comprises of solar PV, wind turbine and micro-hydro as renewable energy sources, diesel generator as the conventional energy source and battery as the storage device. The block diagram of the chosen stand-alone HRES is shown in Fig. 1.

The main objective of any HRES is to maximize the utilization of primary energy sources by considering the other factors like financial investment, running cost, reliability and durability of the considered system [1]. The mathematical modeling of individual components present in HRES is discussed in this section.

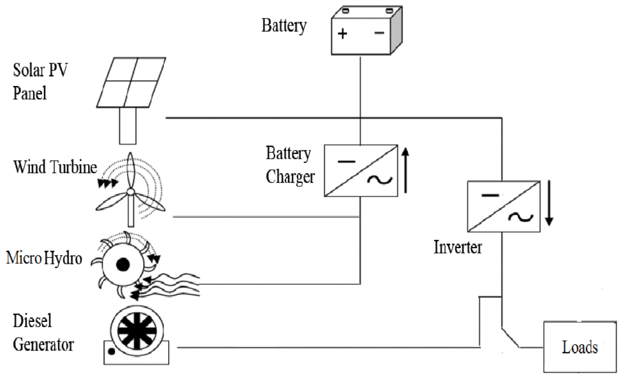


Fig.1. Block diagram of HRES

### 2.1 Solar photovoltaic (solar PV)

The output power produced from the solar PV panels is given by[18] :

$$P_{pv}(t) = \eta \times A_{pv} \times i(t) \qquad (1)$$

where $P_{pv}(t)$ is the power produced at hour $t$ by the solar panel in Watts ($W$), $\eta$ is the energy conversion coefficient in %, $A_{pv}$ is the area of a single PV panel in $m^2$ and $i(t)$ is the isolation at hour $t$ in $W/m^2$.

### 2.2 Wind turbine

The power output from wind turbine which depends on the velocity of the wind is given by [18]:

$$P_w(t) = 0.5 \times \eta_{wt} \times \eta_g \times \rho \times C_p \times A \times v^3(t) \qquad (2)$$

where $P_w(t)$ is the power produced at hour $t$ by the wind turbine in $W$, $\eta_{wt}$ is the efficiency of the wind turbine in %, $\eta_g$ is the efficiency of the generator in %, $\rho$ is the density of air in $kg/m^3$, $C_p$ is the power coefficient of wind turbine, $A$ is the wind turbine rotor swept area in $m^2$ and $v(t)$ is the velocity of the wind in $m/s$.

### 2.3 Micro-hydro turbine

The hydro unit plays a crucial role in secure, reliable and profitable operation of power system by supplying for the power uncertainty. The output power from the micro- hydro turbine is given by [18]:

$$P_h(t) = \eta_h \times g \times \rho_w \times H \times Q(t) \qquad (3)$$

where $P_h(t)$ is the power produced at hour $t$ by the hydro turbine in $W$, $\eta_h$ is the efficiency of the hydro turbine in %, $g$ is the acceleration due to gravity in $m/s^2$, $\rho_w$ is the density of water in $kg/m^3$, $H$ is the effective head in $m$ and $Q(t)$ is the flow rate of water at hour $t$ in liters / second ($l/s$).

### 2.4 Battery

The battery gets charged or discharged based on the power produced by the primary energy sources i.e., renewable energy sources. If the total energy produced by the primary energy sources is greater than the demand for a particular hour then the battery gets charged and similarly if the total energy produced by the primary energy sources is lesser than the demand for a particular hour then the battery gets discharged [18] . The total energy produced by the primary energy sources is given by

$$P_p(t) = \eta_i \times [N_{pv} P_{pv}(t) + N_w P_w(t)] + N_h P_h(t) \quad (4)$$

where $P_p(t)$ is the summation of the energy produced by the primary energy sources in $W$, $\eta_i$ is the efficiency of the inverter in %, $N_{pv}, N_w$ and $N_h$ are the total number of solar panels ,wind turbines and hydro turbines respectively.

The state of charge (SOC) for the battery for a hour is related to the state of charge of battery at the previous hour which is given in Eqn.(5) and Eqn.(6)

$$P_b(t) = P_b(t-1)(1-\sigma) + \left( P_p(t) - \left( \frac{P_L(t)}{\eta_i} \right) \right) \eta_b \text{ if } P_p(t) > P_L(t) \quad (5)$$

$$P_b(t) = P_b(t-1)(1-\sigma) - \left( P_L(t) - \left( \frac{P_p(t)}{\eta_i} \right) \right) \text{ if } P_p(t) < P_L(t) \quad (6)$$

where $P_b(t)$ is the available capacity of battery banks at hour $t$ in $W$, $\sigma$ is the self-discharge rate of the battery banks, $\eta_b$ is the efficiency of a battery in %, and $P_L(t)$ is the demand of the system at hour $t$ in $W$ .

2.5 Diesel generator

When $P_p(t) > P_L(t)$ for a particular hour $t$ and when the battery doesn't have sufficient energy to supply the demand, diesel generator gets operated to generate remaining power. The power generated by diesel generator is, $P_{dg}(t)$ [18].

## 3. Problem formulation

### 3.1 Objective function

The main objective of selected HRES is to minimize the total annual cost of the system, $TC_{annual}$ which is given by: [18]

$$\min TC_{annual} = \min CC_{annual} + OC_{annual} \quad (7)$$

where $TC_{annual}$ is the total annual cost in Euro (€), $CC_{annual}$ is the annual capital cost in € and $OC_{annual}$ is the annual operational cost in € of the chosen system.

### 3.2 Annual capital cost calculation

The annual capital cost of the system consists of the capital cost of the units in the chosen hybrid system which does not require replacement and is given by

$$CC_{annual} = CRF \times CC_{units} \quad (8)$$

where $CRF$ is the capital recovery factor of the system and $CC_{units}$ is the summation of capital cost of all the units present in the system in €

#### 3.2.1 Calculation of $CRF$

The $CRF$ of the system is a ratio to calculate the present value of a series of equal cash flows and is calculated as

$$CRF = \frac{i \times (1+i)^N}{(1+i)^N - 1} \quad (9)$$

where $i$ is the interest rate in % and $N$ is the project lifetime in years which are assumed to be $15\%$ and $20$ years respectively in this paper.

#### 3.2.2 Calculation of $CC_{units}$

The capital cost of all the units present in the chosen HRES system is given by,

$$CC_{units} = a + b + c + d + (N_b \times C_b) \quad (10)$$

where $a = \sum_{i=1}^{N_{pv}} (C_{pv} \times P_{pvr})$, $b = \sum_{i=1}^{N_w} (C_w \times P_{wr})$, $c = \sum_{i=1}^{N_h} (C_h \times P_{hr})$

$d = \sum_{i=1}^{N_d} (C_d \times P_{dr})$, $N_d$ is the number of diesel generators, $N_b$ is the number of batteries, $C_b$ is the capital cost of battery in €, $C_{pv}, C_w, C_h$ and $C_d$ are the cost per $kW$ of generated by solar PV , wind, micro-hydro and diesel generator respectively in €, $P_{pvr}$, $P_{wr}$, $P_{hr}$ and $P_{dr}$ are the rated power of solar PV, wind, micro-hydro and diesel generator in $W$ respectively.

### 3.3 Annual operational cost calculation

The annual operational cost for the HRES system is given by

$$OC_{annual} = 365 \times DOC \quad (11)$$

where $DOC$ is the daily operational cost of the system in € which is the summation of operational cost of batteries, diesel generators, fuel used and renewable energy units which is given by

$$DOC = O_{pv} P_{pvt} + O_h P_{ht} + O_w P_{wt} + O_b P_{bt} + O_d P_{dt} + F_d \times F_t \quad (12)$$

where $O_{pv}$, $O_w$, $O_h$, $O_b$, $O_d$ and $F_d$ are the operational cost of solar PV, wind, hydro, diesel generator, battery per $kWh$ and fuel cost respectively in €, $P_{pvt}$, $P_{wt}$, $P_{ht}$, $P_{dt}$ and $P_{bt}$ are the total power generated from solar PV, wind, hydro, diesel generator and battery in a day in $W$ and $F_t$ is the total fuel consumed in a day in $liters(l)$ which is given by

$$F_t = \sum_{t=1}^{24} F(t) \quad (13)$$

where $F(t) = 0.246 \times P_d(t) + N_d \times 0.8415 \times P_{drated}$ is the fuel consumption at hour $t$ in $l$ .

### 3.3 Design constraints

#### 3.3.1 Inequality constraints

a) Number of devices

The number of wind power generation, PV panels, batteries, diesel generators and micro-hydro plants are subjected to following constraints:

$0 \le N_w \le N_{wm}$, $0 \le N_{pv} \le N_{pvm}$, $0 \le N_h \le N_{hm}$ $0 \le N_d \le N_{dm}$ and $0 \le N_b \le N_{bm}$ (14)

where $N_{wm}$, $N_{pvm}$, $N_{hm}$, $N_{dm}$ and $N_{bm}$ are the maximum number of wind turbines, PV panels, hydro turbines, diesel generators and batteries that can be incorporated in the system respectively.

b) Available capacity of battery banks

$$P_{bmin} \le P_b(t) \le P_{bmax} \quad (15)$$

where $P_{bmin}, P_{bmax}$ are the minimum and maximum allowed energy level in the battery banks.

3.3.2 Equality constraints

$$P_{pv}(t) + P_w(t) + P_h(t) + P_{b1}(t) + P_d(t) = P_L(t) \quad (16)$$

## 4. Differential evolution (DE) algorithm

DE algorithm, a promising global search method was first proposed by Storn and Price in 1995 and has been widely used in solving optimization problems in various engineering fields. The success of DE algorithm over a decade is due to its ability to handle nonlinear and multimodal real time problems. According to Storn and Price, the operations in DE algorithm can be described in four main phases as follows [7][19][20].

### 4.1 Initialization of parameter vectors

The DE algorithm starts with initialization of parameter vectors or target vector of decision variables $D$ based on their upper bound $X_{\max}$ and lower bound $X_{\min}$ where $X_{min} = \left(x_{min}^1, ..., x_{min}^D\right)$ and $X_{max} = \left(x_{max}^1, ..., x_{max}^D\right)$, $x_{min}^j$ is the minimum value of the decision variable $j$ and $x_{max}^j$ is the maximum value of the decision variable $j$ , $j = 1,2,...,D$. The initial population vector in DE - PAS algorithm represented as $X_{i,G} = \left(x_{i,G}^1, x_{i,G}^2, ..., x_{i,G}^D\right)$, where $i = 1,2,...,N$ and $G$ represents the current generation is initialized using

$$x_{i,G}^j = x_{min}^j + rand\left(x_{max}^j - x_{min}^j\right) \quad (17)$$

where $rand$ is a uniformly distributed random number lying between 0 and 1 and $x_{i,G}^j$ is the value of $j^{\text{th}}$ decision variable in population $i$.

### 4.2 Mutation

In mutation phase of DE, new parameter vectors or mutant vector are generated by adding the weighted difference of two parameter vectors to a third vector. There exist different method for DE algorithm to generate the mutant vector and are listed in [7]. In this paper, the following methods are used.

$$\text{DE/best/1:} \; V_{i,G} = X_{best,G} + F\left(X_{r_1,G} - X_{r_2,G}\right) \quad (18)$$

$$\text{DE/rand/1} \; V_{i,G} = X_{r_1,G} + F\left(X_{r_2,G} - X_{r_3,G}\right) \quad (19)$$

where $r_{1,G}, r_{2,G}$ and $r_{3,G}$ are mutually exclusive integers which are randomly generated within $[1, N]$ which also differs from index $i$ such that $r_{1,G} \ne r_{2,G} \ne r_{3,G} \ne i$. The scaling factor or mutation factor $F$ is a positive control parameter for scaling the difference vector is in the range $0 < F \le 1.2$. $X_{best,G}$ is the best individual target vector with the best fitness in the population of the current generation $G$ and the mutant vector $V_{i,G} = \left(v_{i,G}^1, v_{i,G}^2, ..., v_{i,G}^D\right)$ where $v_{i,G}^j$ is the mutant vector of decision variable $j$ in vector $i$.

### 4.3 Crossover

Similar to other well known algorithm, the crossover operation in DE is performed to maintain population diversity for the next generation In De, the trial vector $U_{i,G}$ where $U_{i,G} = \left[u_{i,G}^1, u_{i,G}^2, ..., u_{i,G}^D\right]$, $u_{i,G}^j$ is the trial vector of decision variable $j$ in the vector $i$ is produced from mutant vector and parameter vector using the following scheme[20]

$$u_{i,G}^j = \begin{cases} v_{i,G}^j & \text{if } rand_i^j \le CR \text{ or } j = j_{rand} \\ x_{i,G}^j & \text{otherwise} \end{cases} \quad (20)$$

where $i = 1,2,...,N$, $j = 1,2,...,D$, $CR$ is the crossover rate which is a user-specified constant within the range of 0 and 1 which controls the fraction of variables to be copied from the mutant vector, $rand_i^j$ is the randomly generated number between 0 and 1 and $j_{rand}$ is the randomly chosen integer in the range $[1, D]$ which ensures that trial vector $U_{i,G}$ differs from its target or parameter vector.

### 4.4 Selection

Selection is the last process in DE algorithm which decides whether the trial vector $U_{i,G}$ becomes the member of the parameter vector in the next generation. The one-to-one greedy selection scheme which is applied in DE algorithm is given by [19]:

$$X_{i,G+1} = \begin{cases} U_{i,G} & \text{if } f\left(U_{i,G}\right) \le f\left(X_{i,G}\right) \\ X_{i,G} & \text{otherwise} \end{cases} \quad (21)$$

where $f\left(U_{i,G}\right)$ and $f\left(X_{i,G}\right)$ are the fitness values of $U_{i,G}$ and $X_{i,G}$.

### 4.5 Terminating condition

The terminating condition which is used in this paper for a DE - PAS algorithm is fixing a certain number of generations $G_{max}$ as 100. It is to be noted that all the vectors: parameter, mutant and trial vector must satisfy the constraints.

## 5. Proposed DE-PAS algorithm

### 5.1 Effect of control parameters in proposed DE - PAS algorithm

The main control parameters in DE - PAS algorithm and its variants are $F$ and $CR$[7]. The efficiency and effectiveness of DE algorithm depends on the choice of these parameters. SA technique for these parameters is necessary since the former regulates the step size taken during mutation and latter regulates the search variables inherited by offspring from parent during recombination process [10]. The reports from the empirical analysis in [7] shows that in many optimization problem, setting the parameter value $F \geq 0.6$ and $CR \geq 0.6$ leads to better performance of the DE algorithm. In common, to achieve the effectiveness of DE - PAS algorithm, trial-and-error method was used select the optimal $F$ and $CR$ value. This trial-and-error method leads to huge computational cost and larger computational time[7] [22]. Two modifications were introduced in DE algorithm to overcome these limitations to enhance the searching capability and to increase the convergence speed of the algorithm. The details of the modification is present in the following section and DE algorithm with these modifications is called as differential evolution with parameter adaptation strategy (DE-PAS) which is proposed and implemented in this paper

### 5.2 Adaption techniques for mutation rate, $F$

The typical values of choosing the mutation rate manually has been suggested by various researchers and is illustrated in [11]. Inappropriate choice of mutation rate may lead to premature convergence or stagnation i.e., small mutation rate leads to premature convergence and large mutation rate slow down the search [9] . Therefore, interest in SA techniques to tune the control parameters has been increased among the researchers. The various researchers who used the SA technique for mutation rate is listed in [7]. The fitness based adaptation technique proposed by [15] is used in the proposed DE-PAS algorithm and is given by

$$F_{G+1} = \begin{cases} \max\left\{ l_{\min}, 1 - \left| \dfrac{f_{\max}}{f_{\min}} \right| \right\} & \text{if} \left| \dfrac{f_{\max}}{f_{\min}} \right| < 1, \\ \max\left\{ l_{\min}, 1 - \left| \dfrac{f_{\min}}{f_{\max}} \right| \right\} & \text{otherwise} \end{cases} \tag{22}$$

where $l_{\min} = 0.4$ is the lower bound of $F$, $f_{\min}$ and $f_{\max}$ are the minimum and maximum objective function values in the particular generations. Using this scheme, the search gets diversified at early stages and gets intensified at latter stages. The reason for using this strategy in proposed DE-PAS algorithm for the chosen HRES problem are i) it considers both the extremity fitness values (i.e., maximum fitness value and minimum fitness value) of the objective function, ii) it doesn't include any random values in the scheme and iii) it limits the range of $F$ between 0.4 and 1.

### 5.3 Adaptation technique for crossover rate, $CR$

Similar to the choice of mutation rate, the crossover rate has a significant impact on the success of DE - PAS algorithm but the fact is $CR$ is usually more sensitive to problems with different characteristics [22]. As a matter of fact, if $CR$ is small, it increases the stagnation problem and slows the search process and on the other hand, if $CR$ is assigned a higher value, it increases the population diversity. Therefore, the value of $CR$ should be within a specific range so that, the algorithm doesn't exceeds the diversity level, increases the convergence rate and prevents the stagnation problem [24]. Different $CR$ adaptation strategy was suggested by various researchers to avoid these problems. The SA scheme suggested in [12] is used in the proposed DE-PAS algorithm and is given by:

$$CR_{i,G+1} = \begin{cases} rand_1 & rand_2 \leq \tau_2 \\ C_{i,G} & \text{otherwise} \end{cases} \tag{23}$$

where $CR_{i,G+1}$ is the crossover rate for the next generation, $CR_{i,G}$ is the crossover rate of the current generation. In this paper, it is assumed that $\tau_2 = 0.1$. It assigns a $CR$ value to each of the individual in a population and the better $CR$ values are more likely to survive and produce offspring's which leads to faster convergence of the algorithm. The flowchart of the proposed DE-PAS algorithm is given in Fig. 2.

## 6. Implementation of proposed DE-PAS algorithm for the chosen HRES problem

The implementation of proposed DE-PAS algorithm for the chosen HRES problem is given below:

**Step 1:** For the chosen HRES problem, read the input data to compute the total annual cost of the system.

**Step 2:** Initialization of DE-PAS i.e., population size $N$, $l_{\min} = 0.4$, $CR_{i,G} = 0.5$ and select the stopping criteria.

**Step 3:** Select the number of design variables, $D$ and initialize the design variables i.e., the number of renewable energy sources in the chosen system. In accordance to the population size, the design variable is generated randomly within the limits using Eqn. (24).

$$P_{ij} = P_{i,\min} + rand(1) \times (P_{i,\max} - P_{i,\min}) \tag{24}$$

where $j = 1,2,...,N$, $i = 1,2,...,D$

Therefore, the matrix of $D \times N$ is initialized using Eqn.(24).

**Step 4:** The fitness of each population is calculated using $TC_{annual}$

**Step 5:** Apply the DE-PAS operators to the system i.e., $DE/rand/1$ mutation method, binomial crossover and one-to-one greedy selection method .

**Step 6:** Use fitness based adaptation strategy and SA based adaptation strategy to update the value of $F$ and $CR$ for the next generation.

**Step 7:** Select the termination criterion

Step 4 to step 7 will be repeated till the termination criteria is reached by the algorithm.

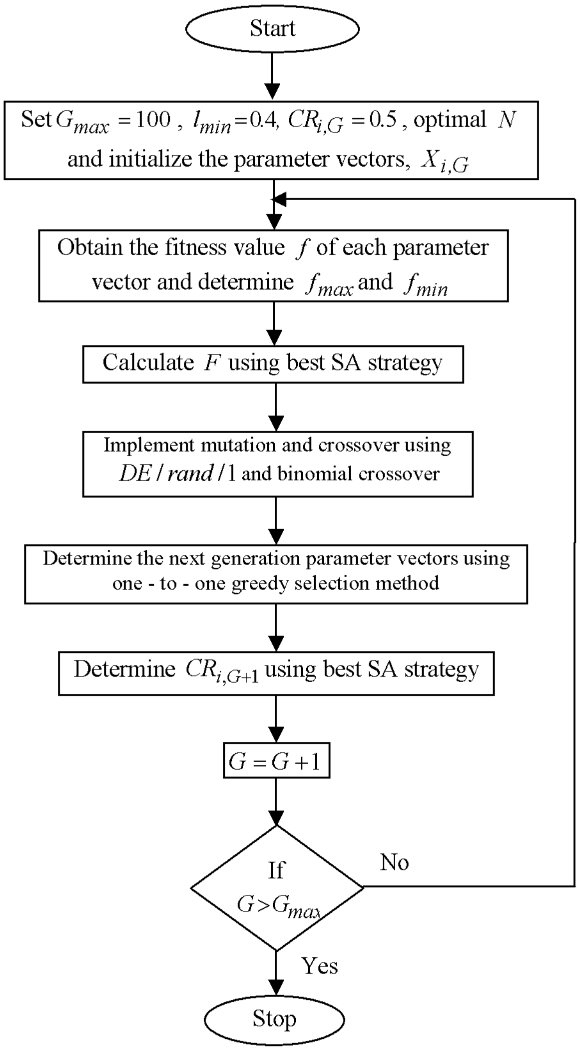


Fig. 2. Flowchart of DE-PAS Algorithm

## 7. Results and discussion

The proposed DE - PAS algorithm is implemented to the chosen HRES to optimize the number of individual renewable energy sources required to meet the demand by minimizing the total cost of the system. The GWO algorithm for different test system has been implemented in MATLAB 2013a on Intel (R) Core (TM) i7 - 3517U CPU 2.40 GHz with 8G-RAM.

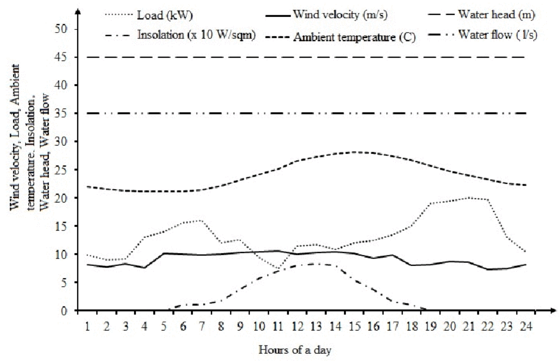


Fig. 3. Input data for HRES

In this paper, the proposed DE-PAS algorithm is to minimize the cost of renewable energy sources for a typical farming village of Western Ghats in Kerala, India by satisfying the electric demand . Micro-hydro, wind and solar PV units which are available and suitable to the resource measurements are selected for unit sizing for the benefit of service and maintenance. The input values to calculate the cost is shown in Fig. 3. The total cost of the system is calculated using Eqn. (7) to Eqn. (13) based on the economical parameters given in [18]. The combination of energy sources and their corresponding total cost obtained using different algorithms is listed in Table.1

Table 1.
Results obtained from different algorithm

| Algorithms | $N_{pv}$ | $N_h$ | $N_w$ | $N_b$ | $N_d$ | Total cost in € |
|---|---|---|---|---|---|---|
| GA | 13 | 1 | 9 | 0 | 0 | 8446.3 |
| PSO | 3 | 0 | 4 | 16 | 3 | 6537.4 |
| DE | 19 | 0 | 6 | 22 | 0 | 5870.2 |
| Trigonometric DE | 0 | 0 | 8 | 25 | 0 | 5535.1 |
| SADE | 1 | 0 | 6 | 20 | 0 | 5124.0 |
| DE-PAS | 0 | 0 | 7 | 22 | 0 | 4762.3 |

The minimum cost achieved by the proposed algorithm is 4762.36 € and the power generated by the renewable energy sources using DE-PAS algorithm is presented in Fig. 4.

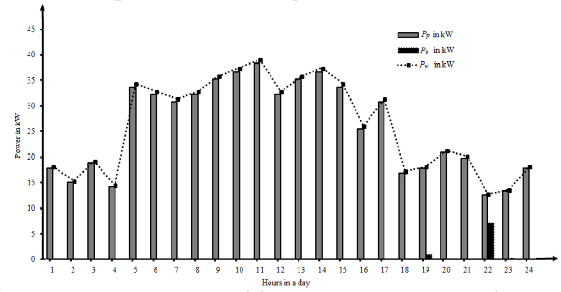


Fig.4. Power generated by energy source using DE-PAS algorithm

The statistical data obtained using different algorithms along with the proposed DE-PAS algorithm is listed in Fig. 4. The efficiency of proposed DE-PAS algorithm for the selected HRES problem is demonstrated by conducting 50 test runs for different algorithm and the results obtained is presented in Fig. 5.

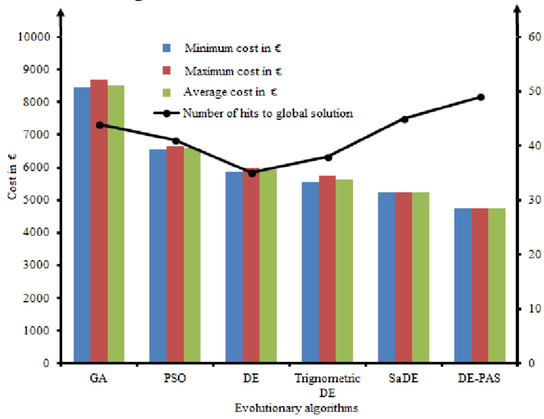

Fig. 5. Comparison of different algorithms

7.1 Result analysis

The success of any optimization algorithm depends on the optimal choice of its parameter. For this problem, to get the optimal parameters $N$, $CR$ and $F$ of the proposed DE-PAS algorithm, the influence of these factors on the optimal solutions is evaluated.

7.1.1 Population size, $N$

Population size $N$ is one of the most significant parameter as the success, effectiveness and efficiency of DE-PAS algorithm depends on it. For an algorithm to implement in a particular problem, an optimal population size $N$ is required to avoid premature convergence, large computational time and to have good solution quality. The range of $N$ varies from $2D$ to $40D$ considering the speed and reliability of the algorithm [21]. Here, the DE-PAS algorithm for the selected HRES problem is tested with different population size. Figure 6 presents the statistical data obtained for the different population size. Minimum cost and computational time for different population size is obtained for single test run and the other statistical data are obtained for 50 test runs. It can be inferred from Fig. 7 that for the selected HRES using DE-PAS the optimal population size is 100. The convergence graph for different population size using DE-PAS algorithm is shown in Fig. 7.

7.1.2 Influence of $F$ and $CR$

The searching accuracy, and convergence speed of DE-PAS algorithm is sensitive to the choice of $F$ and $CR$. However, there is no suitable method or technique for setting these parameters for a particular problem [8].

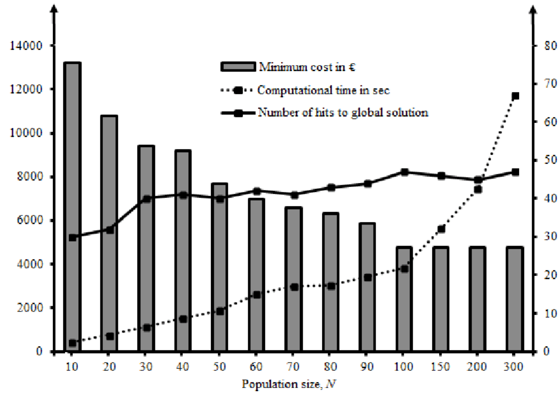

Fig. 6 .Statistical data for different $N$

As perceived from the literatures over the past decade, many claims and counter - claims have been reported regarding the choice of suitable values of the parameters or regarding the tuning and adaption strategies of these parameters. Proper choice of value or tuning strategy of the parameters is necessary as the objective function of a system is sensitive to them [10]. The influence on the choice of $F$ is shown Fig. 8 and Fig. 9 and the impact of $CR$ in

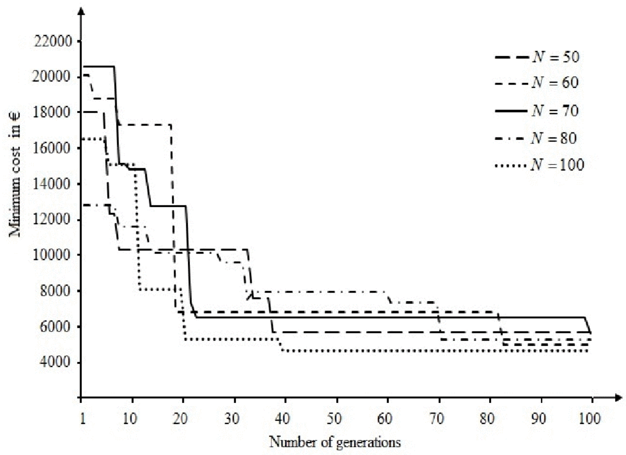

Fig. 7. Convergence graph for different $N$

the proposed DE-PAS algorithm for the selected problem is shown in Fig. 9 and Fig.10. It can be inferred from Fig. 8 and Fig. 9 , that a optimal setting of $CR$ and $F$ is required to minimize the total cost of the selected HRES. The main advantage of the proposed DE-PAS algorithm, is the user does not need manual tune these parameter to get the minimum cost. The parameter adaptation strategy used in the proposed DE-PAS will automatically tune to the optimal value of $CR$ and $F$ irrespective of the initial value given by the user. The choice of parameter adaptation strategy for $CR$ and $F$ is discussed in the following section.

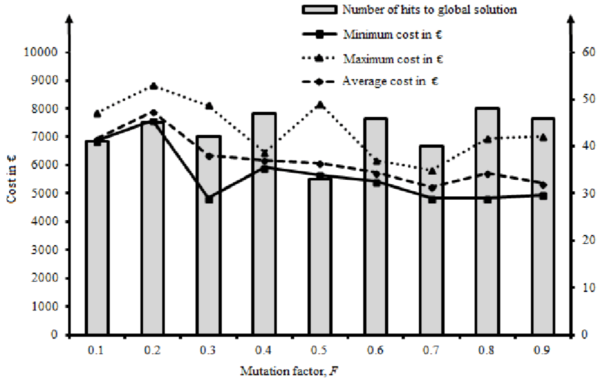


Fig. 8. Influence of mutation factor $F$

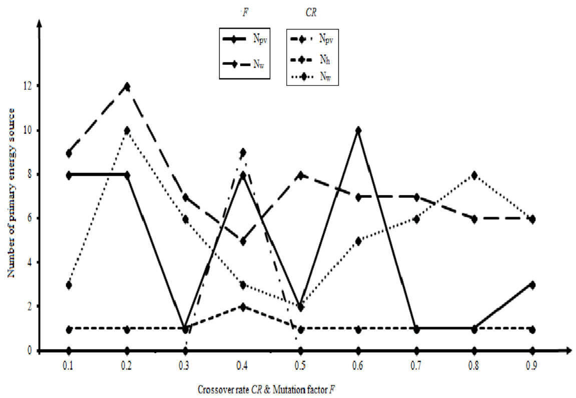


Fig. 9. Influence on decision variables for $CR$ and $F$

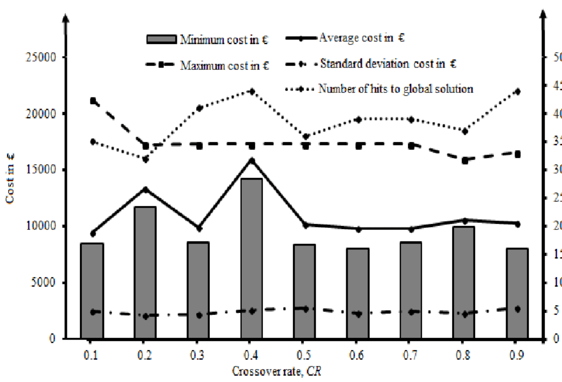


Fig. 10. Impact of crossover rate $CR$

7.1.3 Selection of parameter adaptation strategy for $CR$ and $F$

Different parameter adaptation scheme has been categorized and presented in [20] to overcome difficulties in trial-and-error approach of choosing optimal value of $CR$ and $F$. Self-adaptation technique eliminates the requirement of the trial-and-error parameter tuning and inherently focuses the search towards the appropriate regions [3]. Inappropriate choice of mutation rate may lead to premature convergence or stagnation [9]. Therefore, interest in self-adaptation techniques to tune the control parameters has been increased among the researchers. In this paper, the four different mutation rate adaptation schemes are compared by implementing it in the proposed DE-PAS algorithm for the selected HRES problem. In order to have a significant comparison over the schemes, same values are assigned to the parameters in DE algorithm. The statistical results obtained from DE-PAS algorithm is given in Fig. 11 and the convergence characteristics of different strategies is shown in Fig. 12.

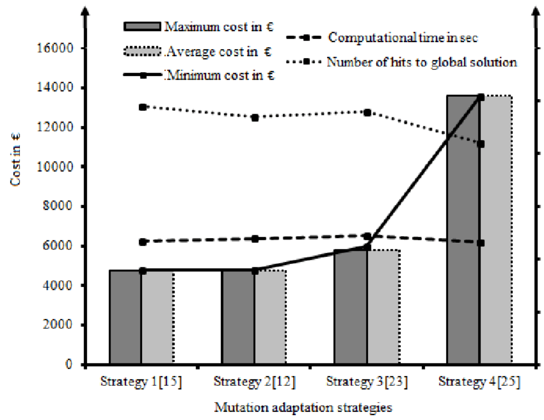


Fig. 11. Comparison of different $F$ adaptation strategies

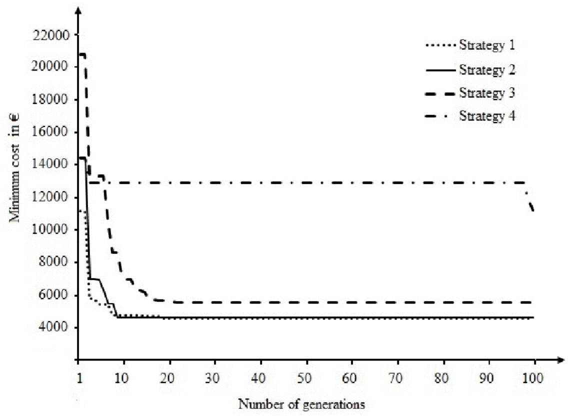


Fig. 12. Convergence characteristics of different $F$ adaptation strategies

Similarly, three crossover rate $CR$ adaptation schemes are implemented in the proposed DE-PAS algorithm for the selected problem for comparison. In order to have a significant comparison over the SA schemes same values are assigned to the parameters in the algorithm. The statistical results obtained from DE-PAS algorithm for various $CR$ adaptation strategies is given in Fig. 13 and the convergence graph is presented in Fig.14.

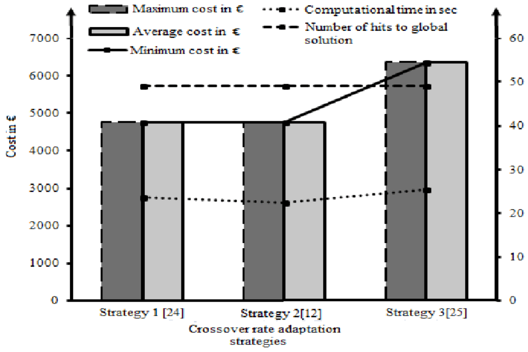


Fig. 13 Statistical data for different *CR* adaptation strategies

7.1.4 Convergence characteristics

The convergence characteristics of the proposed DE-PAS algorithm implemented for the selected HRES problem is shown in Fig. 15. In addition, to reveal the effectiveness of the proposed DE - PAS algorithm, GA, PSO, simple DE, Trignometric DE and self-adaptive DE (SADE) is implemented for the same problem and is shown in Fig. 15.

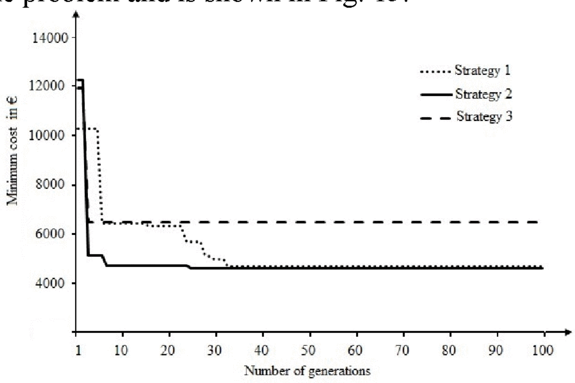


Fig. 14. Convergence characteristics of different *CR* adaptation strategies

The adaptive strategies for *F* and *CR* incorporated in the proposed DE - PAS algorithm, explores the promising regions of the solution space and determine the optimal solution quickly when compared to other state-of-the-art algorithms. The algorithms are implemented for the selected HRES system with the same population size of 100 and maximum number of iterations as 100. The parameters of all the algorithms implemented in this paper are selected in random. The adaptive strategies incorporated in the proposed DE - PAS algorithm eliminates the randomness nature and enforces the algorithm to attain the global solution quickly.

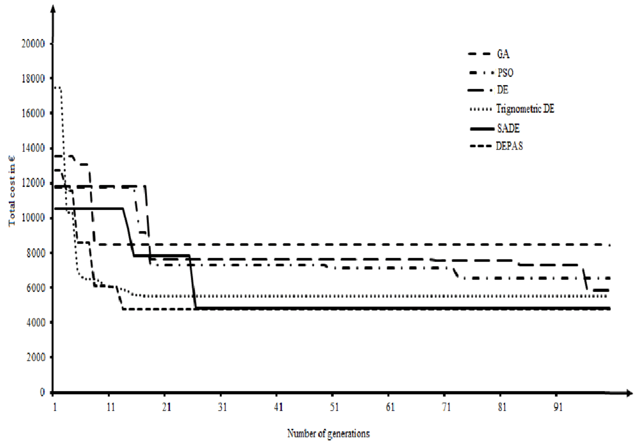


Fig. 15. Convergence characteristics of various algorithms for selected HRES problem

7.1.5 Robustness

The minimum cost achieved by the proposed DE-PAS algorithm for selected HRES test system is given 4762.36 € and it is least when compared with other state-of-the-art algorithms which emphasizes the better solution quality of the proposed algorithm. In general, for any algorithm, its performance cannot be judged through a single trial. Hence, the performance and strength of proposed DE-PAS algorithm is evaluated through number of test runs. Many test runs with different initial population values were performed to test the robustness or the consistency level of the proposed algorithm. The minimum cost attained by the DE-PAS algorithm for the selected test system for 50 different trials is shown in Fig. 16. It can be inferred from Fig. 16 that the proposed DE-PAS algorithm has the capability of achieving the minimum cost more consistently. The general converging characteristic of the proposed DE-PAS algorithm for the test system is shown in Fig. 17. It is observed that after a certain number of generations the difference between the maximum cost and minimum cost is almost the same which gives the strength of the proposed algorithm in solving complex, non-convex type problems.

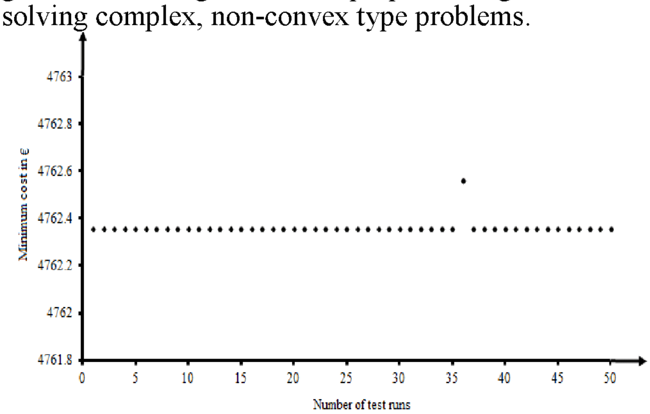


Fig. 16. Robustness of proposed DE-PAS algorithm

## 8. Conclusion

Differential evolution algorithm incorporated with parameter adaptation strategy (DE - PAS) is a simple, efficient, reliable and powerful population based real parameter optimization algorithm widely used in different engineering fields. The performance and success of DE-PAS algorithm depends on its most important control parameters: population size $N$, crossover rate $CR$ and mutation rate $F$. However, there is no separate technique or method to choose these parameters as their best settings varies for different problems and also during the different phase of the algorithm. Different adaptation techniques for these parameters for the HRES problem is studied to determine the most successive adaptation technique and to eliminate the disadvantages of trial-error technique of assigning values to these parameters. The success of fitness based adaptation technique for mutation rate and the SA technique for crossover rate has been studied for the selected HRES problem. The proposed DE-PAS algorithm incorporates these adaptation strategies with an optimal population size to enhance significant superiority of the selected adaptation techniques. The result obtained by implementing the proposed DE - PAS algorithm for the HRES problem shows that the proposed algorithm outperforms the best known variants of DE algorithm and other state-of-the-art algorithms for the given HRES problem.

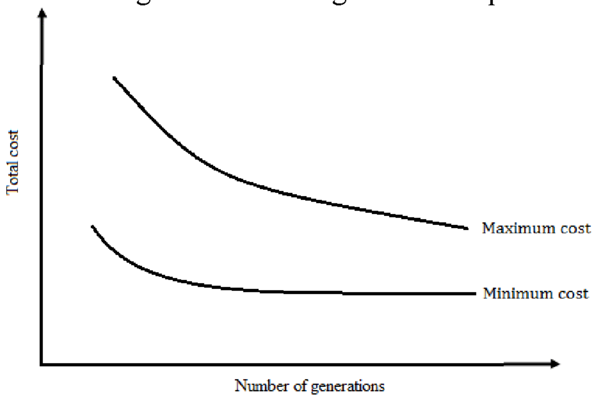


Fig. 17. General convergence characteristics of proposed DE-PAS algorithm

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