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# Optimal Planning of Energy Storage Systems in Transmission Networks using Evolutionary Algorithm

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## ABSTRACT

Nowadays, Renewable Energy Sources (RES) plays an important role in the power grid because of increasing power demand. However, most of the renewable energy sources like wind and solar energies are highly intermittent in nature. The availability of such energy sources varies significantly in different geographical locations. Hence, a grid with high renewable energy penetration needs to build sufficient energy storage to ensure an uninterrupted supply to the end users. This project work will focus on various optimization techniques such as particle swarm optimization (PSO), differential evolution (DE) and real coded genetic algorithm (RCGA) to minimize the total investment involved in planning and storage of energy storage technologies. The proposed work will be implemented in IEEE benchmark systems like IEEE14-bus and IEEE 30-bus systems and the simulation results will be analyzed in detail.

**Keywords:** Energy Storage, Evolutionary Algorithm, Storage Investment Cost, Battery Energy Storage Systems.

## INTRODUCTION

THE Conventional power stations, such as coal-fired, gas and nuclear powered plants, as well as hydroelectric dams and large-scale solar power stations, are centralized and often require electricity to be transmitted over long distances [1]. For the purpose of delivering quality power and uninterrupted supply energy storage comes into role. An Energy Storage System (ESS) has the ability of flexible charging and discharging. Recent development and advances in the ESS and power electronic technologies have made the application of energy storage technologies a viable solution for modern power application. The potential applications mainly cover the following aspects. Through time-shifting, the power generation can be regulated to match the loads [2].

Energy storage systems can buffer the output of intermittent renewable sources and consequently contribute to frequency regulation, system stability, peak shaving, and deferral of transmission line investment [3]. The ESS can also be used to balance the entire grid through ancillary services, load following and load levelling. Moreover, it can meet the increasing requirement of reserves to manage the uncertainty of wind generation which can increase the system operation efficiency, enhance power absorption, achieve fuel cost savings and reduce $CO_2$ emissions. Additionally, the ESS is a potential solution to smooth out the fluctuations and improve supply continuity and power quality [4].

a) Energy storage is the best option for

b) Reducing renewable power curtailment

c) Relieving transmission congestion

Different types of energy storage have different characteristics, including their round-trip efficiency, power and energy rating, self discharge, and investment and maintenance costs. Different types of

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energy storages include Super-capacitors, Flywheels, Chemical batteries, Pumped hydro, Hydrogen, Compressed air energy. Energy storage based on lithium ion battery provides reliable and fast frequency response [5]. This project work uses lithium ion battery as an energy storage because of its high energy density and high round trip efficiency.

Ramping events and scheduling errors of wind power plants are examined and rated energy and power of a grid connected storage unit is determined [6]. Minimization of the hourly social cost and maximization of wind power utilization over a scheduling period is achieved using Probability optimal power flow (POPF) [7]. Increases the wind energy penetration and determines cost of energy produced through ESS for different scenarios using Optimal power flow (OPF) in UK Generic Distribution System [8].

This paper provides an optimization framework for reducing the total investment cost of energy storage systems. The proposed work is optimized using various evolutionary optimization techniques such as Particle swarm optimization (PSO), Real coded genetic algorithm (RCGA) and Differential Evolution (DE). The results of various techniques implemented in the proposed model are compared and suitable technique is identified which provides reduced investment cost of the energy storage systems.

The performance characteristics and the cost analysis of the lithium ion battery is given in the Table I and II.

**TableI.** *Performance Characteristics of Lithium Ion Battery*

| Technology | Lithium Ion |
|---|---|
| Roundtrip Efficiency (%) | 85-98 |
| Self-discharge rate | 0.1-0.3 |
| Cycle Lifetime (cycles) | 1k-10k |
| Lifetime (Years) | 5-15 |
| Specific Energy (W/kg) | 75-200 |
| Specific Power (W/Kg) | 150-315 |
| Energy Density (Wh/L) | 200-500 |

**TableII.** *Cost Analysis of Lithium Ion Battery*

| Technology | Lithium Ion |
|---|---|
| Power Cost ($/kW) | 175-4000 |
| Energy Cost ($/kWh) | 500-2500 |
| BoP Cost ($/kWh) | 120-600 |
| O&M Fixed Cost ($/kW-y) | 12-30 |

## ENERGY STORAGE TECHNOLOGIES

### Overview

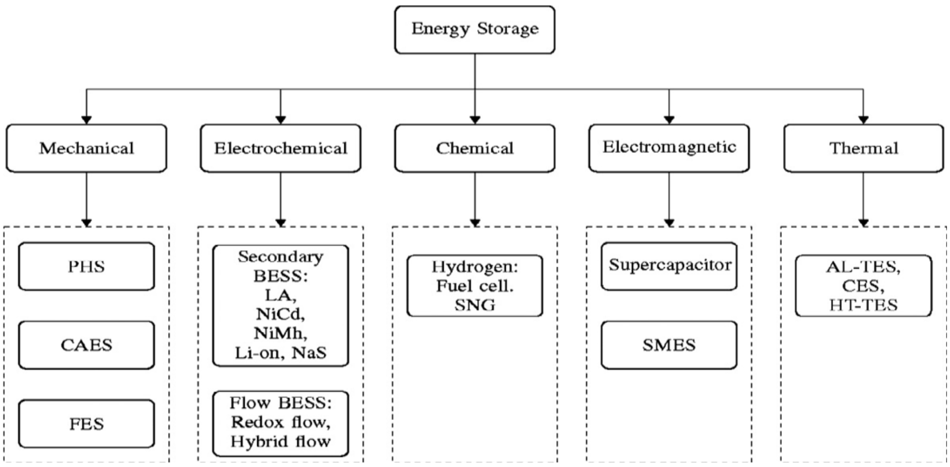


**Fig1.** *Energy Storage Technologies*

The electrical energy can be stored in different energy forms: mechanical, electro-chemical, chemical, electromagnetic, thermal, etc. The classification of energy storage technologies according to the stored energy form is illustrated in Fig.1.

### Battery Energy Storage Systems (BESS)

The BESS stores electricity in the form of chemical energy. A conventional secondary battery consists of a set of low-voltage/ power battery cells connected in parallel and series to achieve a desired electrical characteristic. Each cell is made up of a liquid, paste or solid electrolyte together with anode and cathode. A battery is charged by an internal chemical reaction under a potential applied to both electrodes. The reaction is reversible and the battery delivers the absorbed energy for discharging [13]. Various types of secondary batteries have been developed for commercial use, including Lead Acid (LA) battery, Nickel Cadmium (NiCd) battery, Nickel Metal Hybrid (NiMH) battery, Lithium Ion (Li-ion) battery and Sodium Sulphur (NaS) battery. This project work focuses on Lithium Ion battery (Li-ion).

The rated capacity of modern wind farms can reach to several hundred MWs. For the energy management purpose, large-scale storage medium should be applied, such as Battery Energy Storage Systems (BESS), Pumped Hydro Storage (PHS) and Compressed Air Energy Storage(CAES). Since the PHS and CAES are limited by topographical constraints, the BESS is considered as a more competitive option for large-scale ESS application due to high power and energy density, scalability, fast response, simple maintenance requirement and high cycle life for both technical and economical considerations. The high energy density storage medium, normally BESS, is adopted for low frequency fluctuation mitigation, and the high power density storage mediums, which can be super-capacitor, Super Conducting Magnetic Energy Storage (SMES) , Flywheel Energy Storage (FES) , are used for smoothing high-frequency fluctuations. This paper focus on Lithium Ion Battery Storage system to meet over the objective function of minimization of Total Storage Cost on Transmission Networks.

### Parameters of Li-Ion Battery

| | |
|---|---|
| Specific energy density: | 100 to 250 W·h/kg |
| Specific power density: | 300 to 1500 W/kg |
| Nominal voltage: | 3.7V/Cell |
| Rated current: | 2.9A |
| Life time: | 2 years |
| Charging time: | 2-6 Hours |
| Round trip efficiency: | 85 - 100 |

## ENERGY STORAGE PLANNING

Consider a power network having nodes with demand ($P_{Di}(t)$), dispatchable generation ($P_{Gi}(t)$), connected to them. Storage is defined in accordance with the generator convention, i.e. the storage power is positive during discharge periods and negative during charge periods. In all cases, the index takes value either 1 or 0 with the understanding that any quantity (such as dispatchable generation) when connected to a node is set to 1 & when disconnected from node is set to 0. The objective function used in optimal storage planning problem, for a single scenario of load and renewable generation profiles over times t=1,2,...,24h , comprises of two major terms: the daily cost of operating conventional generation, the storage investment cost per interest period (one year or 365 days) as given in Eqn. (1.1).

$$TSC = \sum_{t=1}^{24}\sum_{i=1}^{n}\sum_{k=1}^{N_i}(c_{ik}P_{Gik}(t) + c_{i0}) + \frac{K_s}{365}\sum_{i=1}^{n}\alpha_i SC_i \tag{1.1}$$

Where the storage investment cost at bus i ($SC_i$) is in function of the rated power and energy of the device, and is a binary variable $\alpha_i$ which takes the value one, if storage is installed at node and zero otherwise.

The physical and technical constraints that govern the energy storage planning problem are listed below in eqn. (1.2) to eqn. (1.5):

Generator dispatch and ramp-rate limits:

$$P_{Gi}(t) = P_{Gi}^{min} + P_{Gi}(t),\ i = 1, \ldots .n, t = 1, \ldots .24 \tag{1.2}$$

$$P_{Gi}^{min} \leq P_{Gi}(t) \leq P_{Gi}^{max} \tag{1.3}$$

DC power flow equations and line flow limits:

$$P_{Gi}(t) - \sum_{j\in\Omega(i)} B_{ij}\theta_{ij}(t) = P_{Di}(t)\ \ i = 1, \ldots n, t = 1, \ldots 24 \tag{1.4}$$

$$-P_{ij}^{max} \leq B_{ij}\theta_{ij}(t) \leq P_{ij}^{max}, j \in \Omega(i)\ \ i = 1, \ldots n, t = 1, \ldots ,24. \tag{1.5}$$

## Nomenclature

$K_s$ Capital recovery factor of storage investment.

n - Number of nodes in the system.

Ni - Number of linear segments in the cost curve of the generator at node .

$P_{Di}(t)$ Power demand at node i and in period t

$P_{Gik}(t)$ Power generation at node i , over segment k , and in period t

$P_{Gi}(t)$ Power generation at node i and in period t

$P_{Gik}^{max}$ Maximum power generation at node i and over segment k

$P_{Gi}^{min}$ Minimum power generation at node

$P_{ij}^{max}$ Maximum power flow limit between nodes i and j

$SC_i$ Storage investment cost at node i

$B_{ij}$ Line susceptance between nodes and, defined as a positive number

$\theta_{ij}(t)$ Difference between nodal angles i and j in period t

### Cost Methodology

The basic cost components of Energy storage system are shown in Figure 2

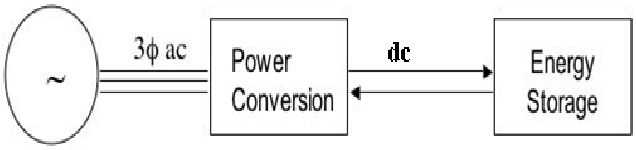


**Figure2.** *Major cost components of the energy storage system*

### Capital Cost

The capital cost calculation, in its simplest form is given by eqn (1.6)

Total Storage Cost ($) = Cost of Power Conversion Unit ($) + Storage Unit Cost (1.6)

The cost of the power conversion equipment is proportional to the power rating of the system as given by eqn. (1.7)

Cost of Power Conversion System (PCS) = PCS Unit Cost ($/MW)*Power (MW) (1.7)

For most systems, the cost of the storage unit is proportional to the amount of energy stored as given by eqn. (1.8)

Cost Storage ($) = Storage Cost per Unit ($/MWh) * Energy Rating (MWh) (1.8)

Where E is the stored energy capacity.

## OPTIMIZATION TECHNIQUES USED FOR ENERGY STORAGE PLANNING

In this work, the proposed optimization model is evaluated using various evolutionary computation techniques such as Real Coded Genetic Algorithm (RCGA), Particle Swarm Optimization (PSO) and Differential Evolution (DE) for minimizing the total storage cost of the energy storage system.

### Real Coded Genetic Algorithm

Genetic Algorithm (GA) belongs to the class of randomized heuristic search techniques. GA is a general purpose search procedure that uses the principles inspired by natural genetic populations to evolve solution (Goldberg 1989). The traditional GA uses binary representation of strings which is not preferred in continuous search space domain. Real Coded Genetic algorithm (RCGA) gives a straightforward representation of chromosomes by directly coding all variables. The chromosome X is represented as X = {PG, $P_{rated}$}, where PG and $P_{rated}$ denotes the size of generation unit and energy storage unit. [13]

Unlike traditional binary coded GA, decision variables can be directly used to compute the fitness value. The RCGA uses selection, crossover and mutation operators to reproduce offspring for the existing population (Wu C et.al 2007). The RCGA coding incorporates Roulette Wheel selection to decide chromosomes for next generation. The selected chromosomes are placed in a matting pool for crossover and mutation operations. The crossover operation enhances the global search property of

GA and mutation operation prevents the permanent loss of any gene value. In this work, Arithmetic Crossover and Polynomial Mutation, has been used to perform crossover and mutation respectively.

The parameters used in RCGA algorithm for the proposed work are listed in the Table 3

**Table3.** *RCGA Parameters*

| Parameters | Range |
|---|---|
| Population Size | 20 |
| Cross over ratio | 0.8 |
| Scaling factor | 0.5 |
| No of Iterations | 100 |

The RCGA algorithm used in this work for minimizing the total storage cost of the energy storage system is briefed herein

The step by step procedure involved in RCGA algorithm for minimizing the total storage cost is enumerated below:

**Step1:** Determine the number of chromosomes, generation, mutation rate and crossover values.

**Step2:** Randomly initialize the population of chromosomes ($P_G$ & $P_{RATED}$) for Energy Storage and computation.

**Step3:** Evaluate the fitness function of chromosomes by calculating the objective function given in Eqn. (1.1)

**Step4:** Perform Tournament selection by Rouletee wheel selection method.

**Step5:** Perform Crossover by Arithmetic Crossover Method.

**Step6:** Perform mutation by polynomial mutation method.

**Step7:** Update the population by moving the offspring to next generation.

**Step8:** Print the obtained optimal Storage cost and computation time.

## Differential Evolution

Differential Evolution, one of the evolutionary optimization techniques, was introduced by Storn and Price in 1995 (Storn and Price 1997). DE is highly effective and suitable for high dimensionality problems, which deals with high nonlinearity and multiple optima. Like any other evolutionary algorithm, DE also starts with random initialization of population vector with uniform distribution in search space. DE has three operations–mutation, crossover and selection (Zhou S 2007).

The crucial idea behind DE is that crossover and mutation are used for generating trial vectors (Kalyani and Swarup 2013). Mutation operation generates new parameter vector by adding the weighted difference between two population vectors to a third vector. Crossover operation mixes the mutated vector with target vector to yield a trial vector. Based on the computation of trial vectors, selection operation decides the survival of new vectors to the next generation. There are several strategies that can be used in DE algorithm. In this work, a commonly used strategy denoted as 'DE/rand/1/bin' have been used (Arya et.al 2011). In this representation, 'rand' indicates a random mutant vector to be chosen; '1' the number of difference vectors used and 'bin' denotes the crossover scheme. Table 4 denotes the parameters used in DE algorithm.

**Table4.** *DE Parameters*

| Parameters | Range |
|---|---|
| Population Size | 30 |
| Cross over ratio | 0.1-0.9 |
| Scaling factor | 0.5 |
| Iteration | 100 |

The DE algorithm used in this work for minimizing the total storage cost of the energy storage system is briefed herein.

The step by step procedure involved in DE algorithm minimizing the total storage cost is enumerated below:

1) Randomly initialize a population of individuals X (PG & $P_{Rated}$) . Specify the DE parameters; difference vector scale factor F = 0.05, minimum and maximum crossover probability $CR_{min}$= 0.1 and $CR_{max}$= 0.9.

2) Evaluate the fitness value of each individual in the population using Eqn (1.1). The fitness value is the total storage cost of the energy storage system.

3) Generate mutant vector for each individual $x_i$ according to Eqn. (1.9)

$$V_i = X_{S_1} + F * (X_{S_2} - X_{S_3}) \tag{1.9}$$

The indices $s_1$, $s_2$ and $s_3$ are randomly chosen from population size. It is important to ensure that these indices are different from each other and also from the running index i.

4) Perform crossover to yield the trial vector u by combining the mutant vector v with target vector x using Eqn. (1.10).

$$U_{ij} = \begin{cases} V_{ij}\, rand(j) \le CR \quad or \quad j = randn(i) \\ X_{ij}\, rand(j) \le CR \quad or \quad j \ne randn(i) \end{cases} \tag{1.10}$$

Where rand (j)∈ [0,1] is the $j^{th}$ evaluation of a uniform random generator number. randn (i)∈ {1, 2, . . . , D} is a randomly chosen index ensuring that $u_i$ gets at least one element form mutant vector, $v_i$. CR is the time varying crossover probability constant determined using (1.11).

$$CR = CR_{\min} - \frac{CR_{\max} - CR_{\min}}{Max.Iterations} * Iteration \tag{1.11}$$

5) Perform selection operation based on fitness value and generate new population. If the trial vector $u_i$ yields a better fitness, then $x_i$ is replaced by $u_i$, else $x_i$ is retained at its old value.

6) If stopping criterion (maximum iterations) is reached, stop and print the optimized parameter set (PG and $P_{rated}$); else increase iteration count and loop to Step 3.

## Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an evolutionary computation technique developed by Kennedy and Eberhart in 1995, inspired by social behavior of birds flocking in a multidimensional space. The system is initialized with a population of random solutions and searches for optima by updating the generations (Kennedy et.al 1995). In PSO, each single solution is called as particle. All particles have fitness value, evaluated by fitness function to be optimized, and have velocities, which direct the flying of the particles (Mostafa et.al 2012). To discover the optimal solution, each and every particle is updated by two 'best' values. The first one called Pbest is the best position particle has achieved so far. The second best value is the overall best value obtained among all particles in the population, called as Gbest. After finding these two best values, each particle changes its velocity and position according to the cognition part (Pbest) and social part (Gbest). The update equations for particle's velocity and position are given by Eqns. (1.12) and (1.13).

$$V_{id}^{k+1} = \omega * V_{id}^{k} + c_1 * rand_1 * (Pbest_{id}^{k} - X_{id}^{k}) + c_2 * rand_1 * (Gbest_{d}^{k} - X_{id}^{k}) \quad (1.12)$$

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k} \quad (1.13)$$

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{Max.Iterations} * Current.Iteration \quad (1.14)$$

Where w is the inertia weight calculated by Eqn. (1.14), $V_{id}$ is the particle velocity, $X_{id}$ is the current particle position (solution), $rand_1$ is a random number between (0, 1), c1 and c2 indicates cognition and social learning factors respectively. The PSO parameters are listed in Table 5

**Table5.** *PSO Parameters*

| Parameters | Range |
|---|---|
| Population Size | 10 |
| C 1 | 1 |
| C2 | 1 |
| $W_{min}$ | 0.8 |
| $W_{max}$ | 0.9 |
| Iteration | 100 |

PSO Algorithm for minimizing the total storage cost

1) Randomly initialize a population of particles with position $X_{id}$ (PG and $P_{Rated}$) and velocities $V_{id}$ of the $i^{th}$ particle in $d^{th}$ dimension.
2) Set the parameters of PSO, $C_1 = C_2 = 2$, $W_{max} = 0.9$, $W_{min} = 0.5$.
3) Evaluate the fitness of each particle in the population with each particle's position (PG and $P_{rated}$) using Eqn (1.1).
4) Compare the current position with particle's previous best experience, Pbest, in terms of fitness value and hence update Pbest for each particle in the population.
5) After updating the Pbest, choose the best value among all the particles in Pbest and call it as Global best, Gbest.
6) Update the particle's velocity using Eqn. (1.12) and clamp to its minimum ($V_{min}$) and maximum ($V_{max}$) limit, whichever violates.
7) Move to the next position of the particle using Eqn. (1.13) bounded to its upper and lower limits.
8) Stop the algorithm and print the near optimal solution *(final Gbest) if termination criterion or maximum iterations are reached; otherwise loop to Step 3 and continue the process.

## IEEE 14 BUS Test Systems

The proposed work of minimization of energy storage investment cost is implemented in IEEE 14 system. The hourly load profile taken for IEEE 14 is given in the Table 6. The constant parameters used in this work is given by $K_p$=400, $K_e$=600, $K_s$=0.03,where $K_p$ is the constant of the power conversion unit, $K_e$ is the constant of the energy storage unit & $K_s$ is the capital recovery factor of storage investment. The active power loss of the network is considered in load demand. The Energy Storage has the rating of 96 MW which can cater out critical loads which includes 30% of maximum peak load.

For dynamic loading conditions the performance of the IEEE 14 bus system is analyzed using optimization tools such as PSO, DE & RCGA. To implement the proposed work the storage units are considered in three different fashions which is given by

**Case1:** Single Energy Storage with maximum Power rating of 96 MW.

**Case2:** Two Energy Storage with maximum Power rating of 32 MW & 64 MW.

**Case3:** Three Energy Storage with maximum power rating of 32 MW, 32 MW & 32 MW.

**Table6.** *Hourly Load Data for IEEE 14 Bus System*

| IEEE 14 | | |
|---|---|---|
| Time in Hours | Percentage Loading of Average Value | Pd in MW |
| 12am – 5am | -10 | 202.3 |
| 6am – 11am | 10 | 261.8 |
| 12pm – 7pm | 15 | 273.7 |
| 8pm – 11pm | 20 | 285.6 |

The performance parameters such as fitness function ($), mean ($), standard deviation and time for convergence (sec) for changing system loading conditions using different optimization techniques such as RCGA, PSO & DE are evaluated. The parameters are evaluated for test system with energy storage units being incorporated in possible discrete combinations of maximum power rating as case 1, case 2 & case 3 and enumerated in Table 7, 8 & 9 respectively. The convergence curves for optimized solution using various evolutionary algorithms are depicted in Fig 3, 4 & 5 for various cases.

**Table7.** *Performance Evaluation for Case 1*

| Algorithm | Demand in MW | Fitness Function ($) | Mean ($) | Standard Deviation | Convergence Time(sec) | Iteration of Convergence |
|---|---|---|---|---|---|---|
| PSO | 202.3 | 33035 | 33235 | 1.6308 | 50.36 | 9 |
| | 261.8 | 33056 | 33200 | 7.357 | 19.73 | 7 |
| | 273.7 | 37035 | 37201 | 1.0969 | 113.79 | 4 |
| | 285.4 | 33011 | 33169 | 1.6170 | 14.11 | 7 |
| DE | 202.3 | 26387 | 26612 | 5.5178 | 24.06 | 2 |
| | 261.8 | **25772** | **26640** | **5.7206** | **24.89** | **1** |
| | 273.7 | 26130 | 26227 | 5.3738 | 23.70 | 2 |
| | 285.4 | 26776 | 27566 | 5.7759 | 23.67 | 2 |
| RCGA | 202.3 | 34533 | 35198 | 1.5445 | 5.03 | 5 |
| | 261.8 | 31848 | 34968 | 1.5858 | 5.03 | 12 |
| | 273.7 | 35759 | 35942 | 2.1609 | 5.43 | 17 |
| | 285.4 | 32461 | 35269 | 1.7188 | 8.98 | 53 |

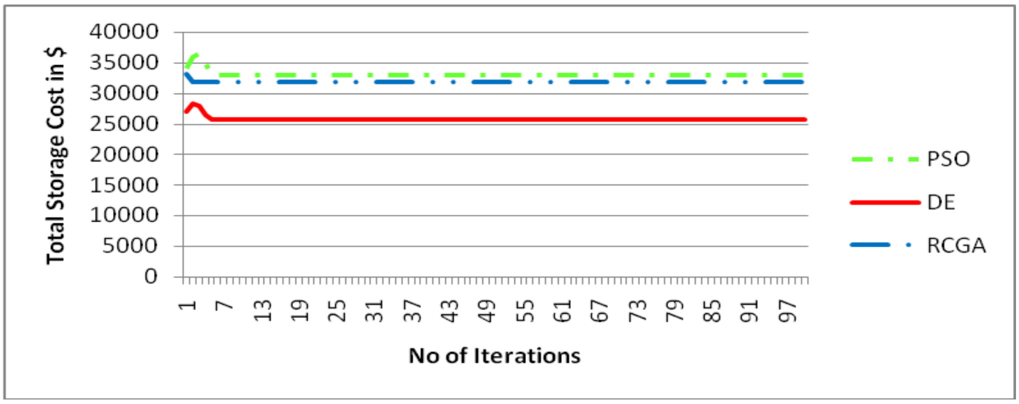


**Fig3.** *Convergence Characteristics for Case 1 for demand 261.8 MW*

**Table8.** *Performance Evaluation for Case 2*

| Algorithm | Demand in MW | Fitness Function ($) | Mean ($) | Standard Deviation | Convergence Time (sec) | Iteration of Convergence |
|---|---|---|---|---|---|---|
| PSO | 202.3 | 31756 | 35381 | 2.0087 | 165.71 | 11 |
| | 261.8 | 28149 | 29433 | 2.1353 | 458.65 | 8 |
| | 273.7 | 30761 | 33319 | 1.8806 | 73.06 | 11 |
| | 285.4 | 27756 | 28219 | 1.2425 | 271.6 | 6 |
| DE | 202.3 | 24439 | 24664 | 4.1456 | 59.81 | 46 |
| | 261.8 | 25064 | 26424 | 5.399 | 56.69 | 74 |
| | 273.7 | **24100** | **24596** | **7.895** | **47.35** | **20** |
| | 285.4 | 25148 | 26321 | 4.5713 | 57.49 | 45 |
| RCGA | 202.3 | 30251 | 31317 | 9.902 | 6.15 | 10 |
| | 261.8 | 30899 | 31940 | 9.839 | 6.92 | 34 |
| | 273.7 | 31216 | 33271 | 9.995 | 5.98 | 14 |
| | 285.4 | 31454 | 33567 | 8.183 | 6.96 | 34 |


**Fig4.** *Convergence Characteristics for Case 2 for demand 273.7 MW*

**Table9.** *Performance Evaluation for Case 3*

| Algorithm | Demand in MW | Fitness Function ($) | Mean ($) | Standard Deviation | Convergence Time (sec) | Iteration of Convergence |
|---|---|---|---|---|---|---|
| PSO | 202.3 | 29316 | 24009 | 5.3051 | 54.79 | 7 |
| | 261.8 | 26539 | 27394 | 3.735 | 285.95 | 15 |
| | 273.7 | 26476 | 30612 | 6.581 | 31.67 | 8 |
| | 285.4 | 33473 | 36999 | 8.914 | 44.56 | 18 |
| DE | 202.3 | 24204 | 24433 | 5.844 | 48.86 | 14 |
| | 261.8 | **23937** | **24551** | **4.762** | **46.13** | **4** |
| | 273.7 | 24726 | 25674 | 5.577 | 45.45 | 7 |
| | 285.4 | 25642 | 27503 | 7.465 | 44.88 | 43 |
| RCGA | 202.3 | 29617 | 30830 | 1.315 | 5.91 | 5 |
| | 261.8 | 29466 | 30821 | 1.414 | 6.01 | 32 |
| | 273.7 | 31420 | 32877 | 1.169 | 5.692 | 38 |
| | 285.4 | 29865 | 30372 | 1.2645 | 6.05 | 4 |

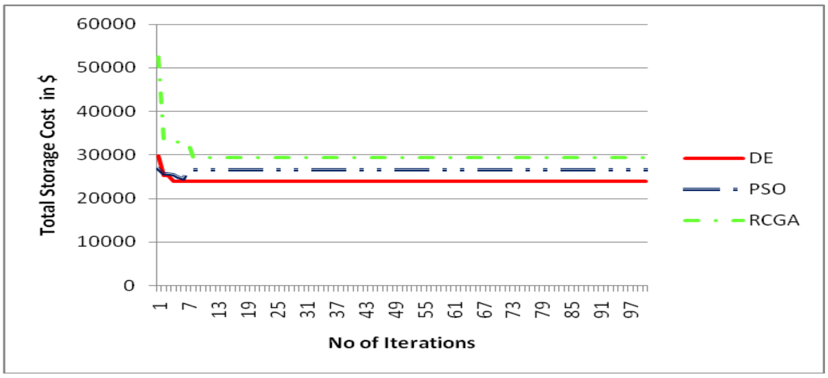


**Fig5.** *Convergence Characteristics for Case 3 for demand 261.8 MW*

On comparing the results obtained by different optimization techniques with changing load scenario and discrete energy storage units, the Differential Evolution (DE) algorithm proves to show promising results and an appropriate tool, compared to other optimization techniques with minimized storage planning cost and outperforms RCGA & PSO.

## IEEE 30 BUS Test Systems

The proposed work of minimization of energy storage investment cost is implemented in IEEE 30 system. The hourly load profile taken for IEEE 30 Bus system is given in the Table 10. The constant parameters used in this work is given by $K_p$=400, $K_e$=600, $K_s$=0.03,where $K_p$ is the constant of the power conversion unit, $K_e$ is the constant of the energy storage unit & $K_s$ is the capital recovery factor of storage investment. The active power loss of the network is considered in load demand. The Energy Storage has the rating of 128 MW which can cater out critical loads which includes 30% of maximum peak load.

For dynamic loading conditions the performance of the IEEE 30 bus system is analyzed by using optimization tools such as PSO, DE & RCGA. To implement the proposed work the storage units are taken in three discrete cases which is given by

**Case1:** Single Energy Storage with maximum Power rating of 128 MW.

**Case2:** Two Energy Storage with maximum Power rating of 32 MW & 96 MW and 64 MW & 64 MW

**Case3:** Three Energy Storage with maximum power rating of 64 MW, 64 MW & 64 MW.

**Table10.** *Hourly Load Profile for IEEE 30 Bus System*

| IEEE 30 | | |
|---|---|---|
| **Time in Hours** | **Percentage Loading of Average Value** | **Pd in MW** |
| 12am – 5am | -10 | 252.25 |
| 6am – 11am | 10 | 260.3 |
| 12pm – 7pm | 15 | 289.4 |
| 8pm – 11pm | 20 | 300.25 |

The performance parameters such as fitness function ($), mean ($), standard deviation and time for convergence (sec) for changing system loading conditions using different optimization techniques such as RCGA, PSO & DE are evaluated. The parameters are evaluated for test system with energy storage units being incorporated in possible discrete combinations of maximum power rating as case 1, case 2 & case 3 and enumerated in Table 11, 12, 13 & 14 respectively. The convergence curves for optimized solution using various evolutionary algorithms are depicted in Fig 6, 7, 8 & 9 for various cases.

**Table11.** *Performance Evaluation for Case 1*

| Algorithm | Demand in MW | Fitness Function ($) | Mean ($) | Standard Deviation | Convergence Time (sec) | Iteration of Convergence |
|---|---|---|---|---|---|---|
| PSO | 252.25 | 36030 | 36077 | 1.0004 | 344.56 | 8 |
| | 260.3 | 37041 | 37084 | 1.333 | 301.39 | 12 |
| | 289.4 | 37529 | 39584 | 1.199 | 200.29 | 16 |
| | 300.25 | 39701 | 41238 | 1.164 | 318.42 | 13 |
| DE | 252.25 | 36161 | 36742 | 1.920 | 147.90 | 1 |
| | 260.3 | 36137 | 36746 | 1.700 | 148.44 | 1 |
| | 289.4 | **35861** | **36125** | **2.069** | **149.89** | **3** |
| | 300.25 | 36179 | 36979 | 2.128 | 149.60 | 2 |
| RCGA | 252.25 | 36996 | 38736 | 6.6610 | 3.77 | 101 |
| | 260.3 | 37258 | 37479 | 7.0921 | 3.67 | 6 |
| | 289.4 | 37181 | 37560 | 7.7871 | 4.32 | 2 |
| | 300.25 | 36556 | 37430 | 7.2603 | 3.71 | 4 |

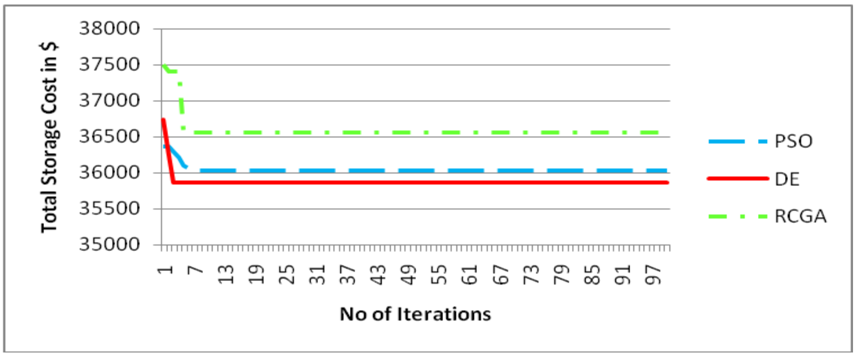


**Fig6.** *Convergence Characteristics for Case 1 for demand 289.4 MW*

**Table12.** *Performance Evaluation for Case 2 (a)*

| Algorithm | Demand in MW | Fitness Function ($) | Mean ($) | Standard Deviation | Convergence Time (sec) | Iteration of Convergence |
|---|---|---|---|---|---|---|
| PSO | 252.25 | 28033 | 30254 | 4.53 | 135.9 | 100 |
| | 260.3 | 27041 | 27084 | 2.504 | 239.28 | 4 |
| | 289.4 | 29577 | 30584 | 6.29 | 301.69 | 13 |
| | 300.25 | 29146 | 29824 | 5.14 | 92.37 | 27 |
| DE | 252.25 | 26387 | 26612 | 5.5178 | 24.06 | 2 |
| | 260.3 | **25102** | **26640** | **5.720** | **24.89** | **1** |
| | 289.4 | 26130 | 26227 | 5.373 | 23.70 | 2 |
| | 300.25 | 26776 | 27566 | 5.775 | 23.67 | 2 |
| RCGA | 252.25 | 36472 | 37491 | 2.685 | 5.92 | 26 |
| | 260.3 | 36482 | 37842 | 4.281 | 5.61 | 5 |
| | 289.4 | 36606 | 37496 | 2.985 | 5.60 | 6 |
| | 300.25 | 36149 | 36420 | 2.764 | 5.72 | 7 |


**Fig7.** *Convergence Characteristics for Case 2(a) for demand 261.8 MW*

**Table13.** *Performance Evaluation for Case 2 (b)*

| Algorithm | Demand in MW | Fitness Function ($) | Mean ($) | Standard Deviation | Convergence Time (sec) | Iteration of Convergence |
|---|---|---|---|---|---|---|
| PSO | 252.25 | **35918** | **36002** | **1.282** | **4.13** | **8** |
| | 260.3 | 36286 | 36370 | 1.278 | 8.31 | 10 |
| | 289.4 | 36291 | 39827 | 1.325 | 43.91 | 13 |
| | 300.25 | 39577 | 40386 | 2.674 | 15.92 | 34 |
| DE | 252.25 | 36122 | 36640 | 1.526 | 18.11 | 1 |
| | 260.3 | 35969 | 36119 | 2.408 | 18.49 | 2 |
| | 289.4 | 36430 | 36870 | 2.212 | 85.89 | 1 |
| | 300.25 | 36073 | 36110 | 3.014 | 84.3 | 2 |
| RCGA | 252.25 | 37434 | 38662 | 4.508 | 4.05 | 34 |
| | 260.3 | 36654 | 36852 | 4.848 | 4.33 | 4 |
| | 289.4 | 36804 | 36976 | 4.137 | 4.07 | 7 |
| | 300.25 | 36861 | 36970 | 4.425 | 4.02 | 10 |

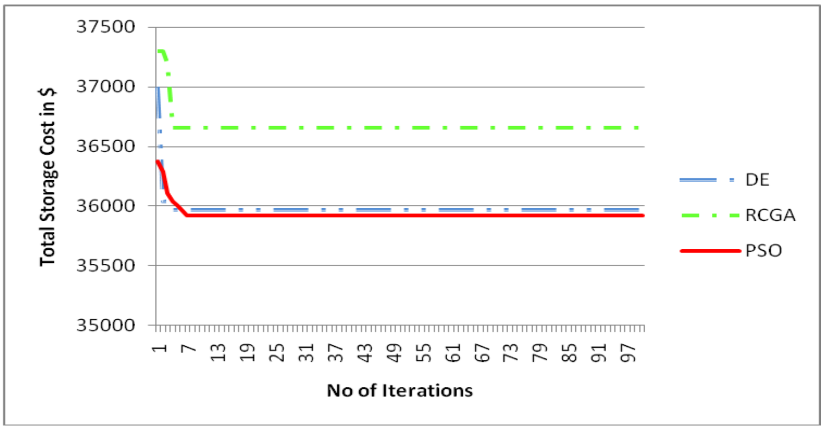


**Fig8.** *Convergence Characteristics for Case 2(b) for demand 252.25 MW*

**Table14.** *Performance Evaluation for Case 3*

| Algorithm | Demand in MW | Fitness Function ($) | Mean ($) | Standard Deviation | Convergence Time (sec) | Iteration of Convergence |
|---|---|---|---|---|---|---|
| PSO | 252.25 | **23916** | **24009** | **5.3051** | **54.79** | **7** |
| | 260.3 | 25639 | 27394 | 3.735 | 285.95 | 15 |
| | 289.4 | 28543 | 30612 | 6.581 | 31.67 | 11 |
| | 300.25 | 33473 | 36999 | 8.914 | 44.56 | 18 |
| DE | 252.25 | 36075 | 36716 | 1.621 | 249.45 | 2 |
| | 260.3 | 35930 | 36052 | 1.243 | 257.57 | 2 |
| | 289.4 | 36294 | 38068 | 1.333 | 250.68 | 1 |
| | 300.25 | 36106 | 36620 | 1.734 | 251.37 | 2 |
| RCGA | 252.25 | 36960 | 39628 | 3.437 | 5.12 | 17 |
| | 260.3 | 36515 | 36670 | 2.575 | 4.36 | 33 |
| | 289.4 | 36638 | 38524 | 3.614 | 4.45 | 4 |
| | 300.25 | 36755 | 38346 | 4.131 | 4.35 | 12 |


**Fig9.** *Convergence Characteristics for Case 3 for demand 252.25 MW*

It is evident from Table 11, 12, 13 & 14 that consistency of each algorithm is measured in terms of statistical parameters namely mean and standard deviation. Further, the near global optimal solution of minimizing the total cost of storage (fitness function) obtained in various algorithms are compared.

On comparing the results of various techniques, the Particle Swarm Optimization (PSO) technique is shown to produce a better performance in terms of minimum fitness function and convergence time per trial in the case of two storage units having capacity of 64 MW & 64 MW and with three storage units. Figure 6, 7, 8 & 9 shows the convergence characteristics of different evolutionary algorithms.

It is also seen from Fig.6 & 7 that DE algorithm outperforms other evolutionary algorithms as it shows a quicker convergence (i.e., only for convergence) and also the value of fitness function is greatly reduced. Overall it is seen that the performance of DE is better compared to other two optimization techniques for both IEEE 14 & IEEE 30 bus systems.

## CONCLUSION

Solving an optimization problem is one of the common scenarios that occur in most engineering applications. The analytical methods are not easy to implement for most of the real-world problems. In fact, for many problems, the curse of dimensionality makes the approach unfeasible to implement. The above issues are of particular importance while solving optimization problems in a power system. As a highly nonlinear, non stationary system with noise and uncertainties, a power network can have a large number of states and parameters. Implementing any of the classical analytical optimization approaches might not be feasible in most of the cases. On the other hand, Evolutionary algorithms like Particle Swarm Optimization (PSO), Differential Evolution (DE) & Real Coded Genetic Algorithm can be an alternative solution. The Optimal Storage Planning in Power System being such a non linear & dynamic problem is solved by utilizing these evolutionary algorithms. The optimal Storage planning is performed in benchmark test systems viz, IEEE 14-bus & IEEE 30-bus system using different optimization tools and the results are evaluated.

On analyzing the results of the test systems, DE proves to be suitable tool for IEEE 14-bus system for discrete combination of different ratings of Energy Storage. For IEEE 30-bus system, the results depicts that PSO outperforms the other tools with changing size and combinations of Energy Storage. By utilizing the suitable tool, the overall Storage planning cost can be reduced and the demand also can be satisfied with enhanced reliability.

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