Optimization of Electrical Generation Cost Using Diferential Evolutionary Algorithm for Large Four Regions Electrical Grid

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Abstract
In this paper, a techno-economic assessment of electrical generation cost optimization for four region large electrical grid is presented. This optimization was attained by using the Differential Evolutionary Algorithm (DEA). The study is the first of its kind as none of the previous studies were conducted in the context of a real fuel value and system constraints. In each of the four large grid regions there is generation fleet with different technology and large load center. The four regions are connected via transmission lines with power flow constraints. The performance of the DEA in optimizing the generation cost is benchmarked with a business as usual (BAU) case. The problem was articulated as a constrained nonlinear problem. The constraints were all real values reflecting the system equipment and component limitations and operation constraints. The results obtained from the research show the efficiency and prospects of the proposed research in optimizing the generation cost. Also addressed in this study is annual cost avoidance from optimization of the study objectives.

Keywords: Differential Evolutionary Algorithm (DEA), generation cost, fuel value, millions of standard cubical feet of gas (MMscf).

Introduction

Electrical generation technology and fuel mix have a large impact on the cost of electricity generation. In this study the Kingdom of Saudi Arabia (KSA)'s electrical grid was modelled as four regions each with its own generation fleet. The effect of availing more gas as part of the fuel mix and introducing more efficient technology in one of the four regions on the generation cost was demonstrated compared to the base case scenario. A Differential Evolutionary Algorithm (DEA) was implemented to identify optimal generation cost given the aforementioned parameters.

Problem Formulation

The problem formulation consists of two parts: the development of the objective functions and the identification of the system electrical constrains to be met; equality and inequality constrains.

Problem Objective Function

The objective to be achieved is the minimization of electricity generation cost J_1 of the generation fleet. This objective function can be expressed in terms of the four region electricity generation cost as follows:

$$J_1 = \text{Minimize (Generation- Value Cost)} = Min \sum_{i=1}^{nl} [\boldsymbol{P}_i^{\mathbf{ER}} + \boldsymbol{P}_i^{\mathbf{CR}} + \boldsymbol{P}_i^{\mathbf{WR}} + \boldsymbol{P}_i^{\mathbf{SR}}] \quad (1)$$

Where nl is the number of generation units in each region, ER, CE, WR and SR are the four generation regions in the KSA electrical grid.

A. Problem Equality and Inequality Constrains

The system constrains are divided into two categories: equality constrains and inequality constrains [1][2]. Details are as follows:

A.1 Equality Constrains

These constrains represent the power load flow equations. The balance between the active power injected PGi, the active power demand PDi and the active power loss Pli at any bus i is equal to zero. The same balance applies for the reactive power QGi, QDi, and Qli. These balances are presented as follows:

$$\text{PGi- PDi - Pli} = 0 \quad (2)$$

$$\text{QGi- QDi - Qli} = 0 \quad (3)$$

The above equations can be detailed as follows:

$$\text{PGi- PDi-}V_i \sum_{\boldsymbol{j=1}}^{\boldsymbol{NB}} \boldsymbol{V_j} \, [\, G_{ij} cos\left(\delta_i\text{-}\delta_j\right) + B_{ij} \sin\left(\delta_i\text{-}\delta_j\right)] = 0 \quad (4)$$

$$QGi - QDi - V_i \sum_{j=1}^{NB} \boldsymbol{V_j} \left[G_{ij} sin\left(\delta_i - \delta_j\right) - B_{ij} \cos\left(\delta_i - \delta_j\right)\right] = 0 \qquad (5)$$

where i = 1, 2, …, NB; NB is the number of buses; PG and QG are the generator real and reactive power, respectively; PD and QD are the load real and reactive power, respectively; Gij and Bij are the conductance and susceptance between bus i and bus j, respectively.

A.2 Inequality Constrains

These constrains represent the system operating constrains posted in Table 1 and they are as follows:

a. The transformers taps.
b. The load buses voltages VL.
c.

Combining the objective function and these constrains, the problem can be mathematically formulated as a nonlinear constrained single objective optimization problem as follows:

Minimize J_I
Subject to:

$$g(x,u) = 0 \qquad (6)$$
$$|h(x,u)| \leq 0 \qquad (7)$$

Where:

x: is the vector of dependent variables consisting of load bus voltage VL and generator reactive power outputs QG. As a result, x can be expressed as

$$x^T = [V_{L1}..V_{LNL}, Q_{Gi}\ldots Q_{GNG}] \qquad (6)$$

u: is the vector of control variables consisting of generator voltages VG and transformer tap settings T. As a result, u can be expressed as

$$u^T = [V_{G1}..V_{GNL}, T_1\ldots T_{NT}] \qquad (8)$$

g: are the equality constrains.
h: are the inequality constrains.

TABLE 1
SYSTEM INEQUALITY CONSTRAINS

Description	Lower Limit	Upper Limit
Generator Unit Terminal Voltage	90%	105%
All Load Buses Voltage	90%	105%
Main Transformer Taps	+16 (+10%)	-16 (-10%)
Generators Step-up Transformer Taps	+8 (+10%)	-8 (-10%)

Differential Evolution Algorithm (DEA) Implementation

The implementation of the DEA technique can be summarized in the following steps [3]-[5]:

1. Generate initial populations of chromosomes; each chromosome consists of genes and each of these genes represents either transformer tap settings, the generation units MW outputs, or the generators voltages values.

2. Assign fitness to each chromosomes, as follows:
   a. Use the Newton-Raphson method to calculate the generation cost for each population.
   b. Identify if the voltage constrains are satisfied.
   c. Assign fitness values to the populations that meet all constrains; the population best power generation fuel cost value (J_1).

3. Identify the best population with its associated chromosomes that has the best objective function value and store it.

4. Apply mutations using the DE/rand/1 mutation technique [4]. Vi (t) - the mutated vector, is created for each population member Xi (t) set by randomly selecting three individuals' x_{r1}, x_{r2} and x_{r3} values and not corresponding to the current individual x_i. Then, a scalar number F is used to scale the difference between any two of the selected individuals. The resultant difference is added to the third selected individual. The mutation process can be written as:

$$V_{i,j}(t) = x_{r1,j}(t) + F * [x_{r2,j}(t) - x_{r3,j}(t)] \qquad (9)$$

   The value of F is usually selected between 0.4 and 1.0. In this study, F was set to be 0.5 (50%). In [14], scaling mutation based on the frequency of successful mutations is applied.

5. Perform the binomial crossover, which can be expressed as follows:

$$u_{i,j}(t) = \begin{cases} v_{i,j}(t) \; if \; rand\;(0,1) < CR \\ x_{i,j}\;(t) \qquad\qquad\qquad else \end{cases} \qquad (10)$$

   CR is the crossover control parameter, and it is usually set within the range [0, 1]. The child $u_{i,j}$ (t) will compete with its parent $x_{i,j}$ (t). CR is set equal to 0.9 (90%) in this study.

6. Perform the selection procedure as described below:

$$x_i(t+1) = u_i(t) \quad \text{condition} \quad f(u_i(t)) \leq f(x_i(t)) \qquad (11)$$

$$x_i(t+1) = x_i(t) \quad \text{condition} \quad f(x_i(t)) \leq f(u_i(t)) \qquad (12)$$

Where $f(\ )$ is the objective function to be minimized.

7. Looping back for the terminating criteria. If the criteria are not fulfilled, then generate new offspring population and begin again.

8. If the termination criteria are met, identify the best population with its associated chromosomes, in terms of minimum real power loss. The DEA evolution process is shown in Figure 1.

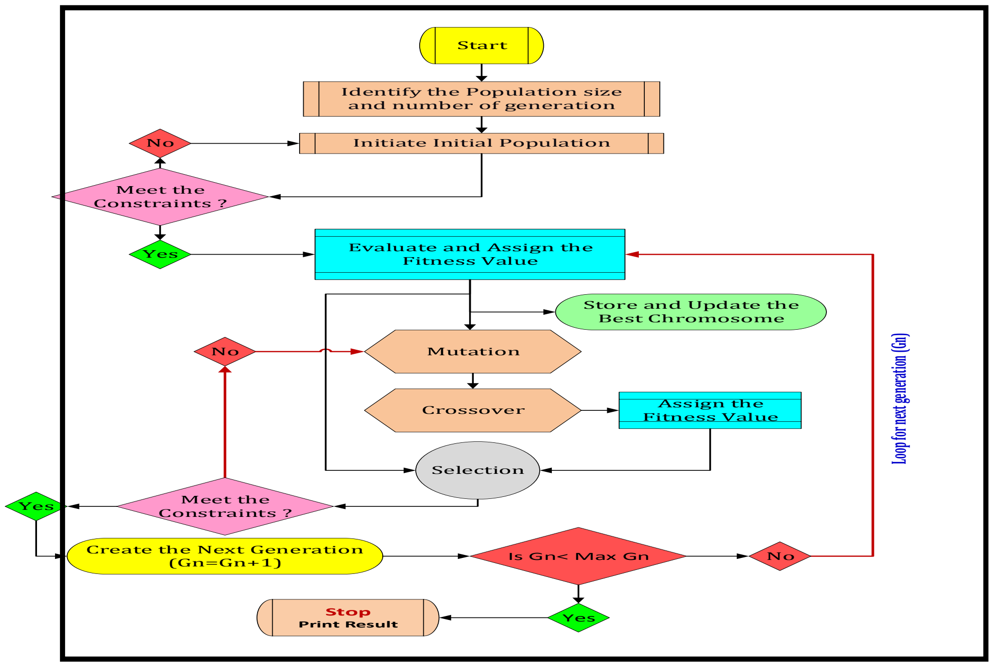

Figure. 1: DEA in single-objective mode evolutionary process chart

Conclusion

The base case scenario (base) is benchmarked against the optimized case scenario (Case-1). In the base case scenario the generation fleet has different technologies and base case fuel mix. In the optimal case, the fleet technologies mix was kept with no change except the introduction of combined cycle (CC) generation at the southern area. Also, more gas were made available, diesel consumption was pushed to zero and Arab Light crude (ALC) fuel was minimized. Figure 2 demonstrates the evolution of the objective function (J_1: total generation cost) to its optimal value. As shown, the objective function converged to its optimal value ($272,187) at the 21st generation.

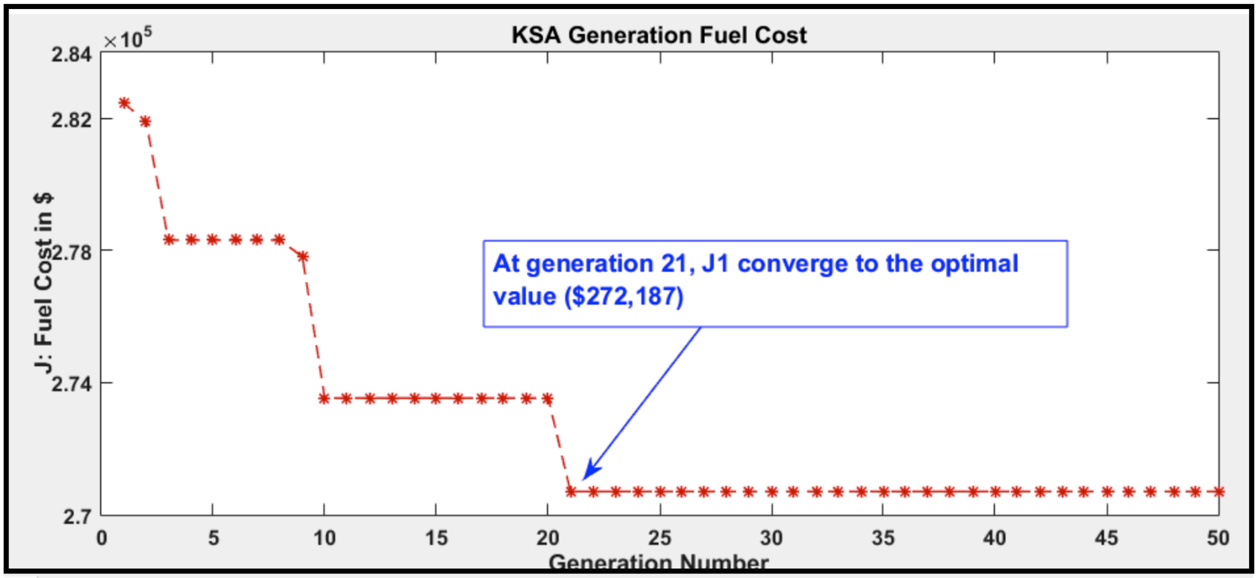

Figure. 2: Evolution of the objective function (J_1) value over 50 generations

The MW distribution among the generation fleet for both scenarios is shown in Figure 3. As you can see, the desalination (DES) and the heat and power plant (CHP) fuel were kept the same for both scenarios as they did not only produce electricity.

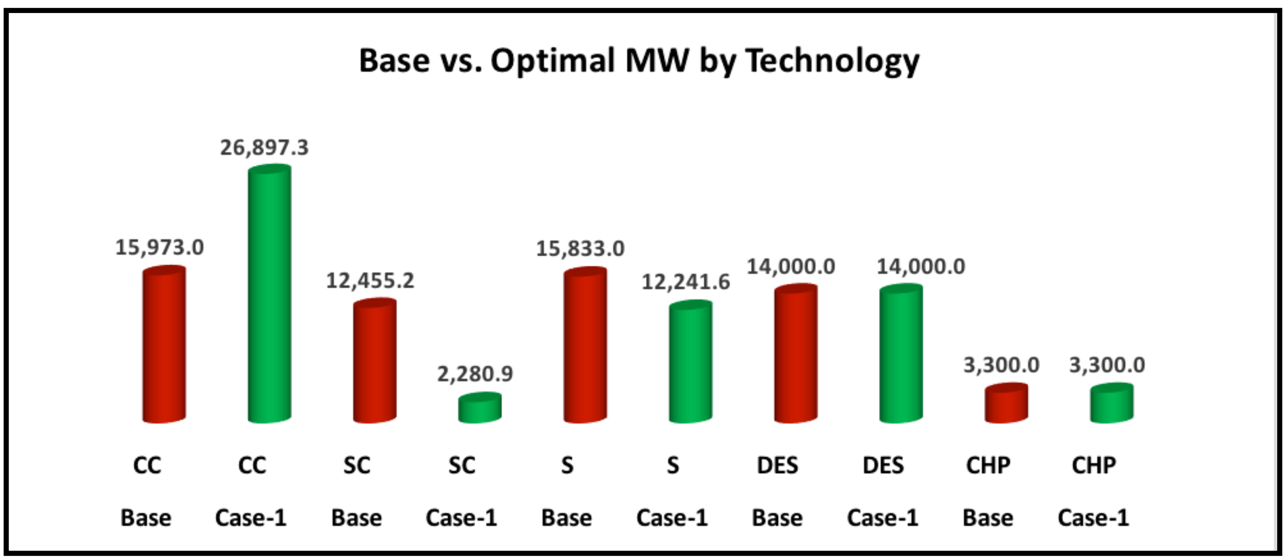

Figure. 3: Base case vs. optimized case senario generation MW distribution

Figure 4 shows the generation cost by technology for the two scenarios. The DES plant fuel consumption was assumed zero for both scenarios and the CHP was kept the same as stated earlier.

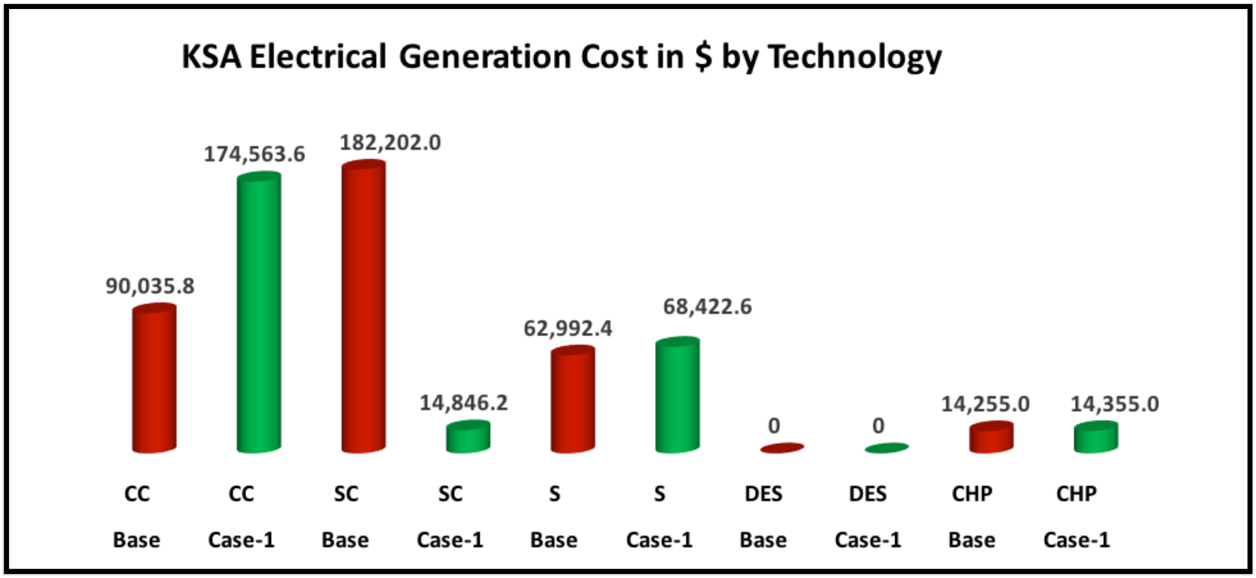

Figure. 4: Base case vs. optimized case senario generation fuel distribution

The total reduction in the generation cost comparing the base case to the optimal case is -22% as shown in Figure 5. The generation cost is reduced from 7.79 $/MWh to 6.1 $/MWh.

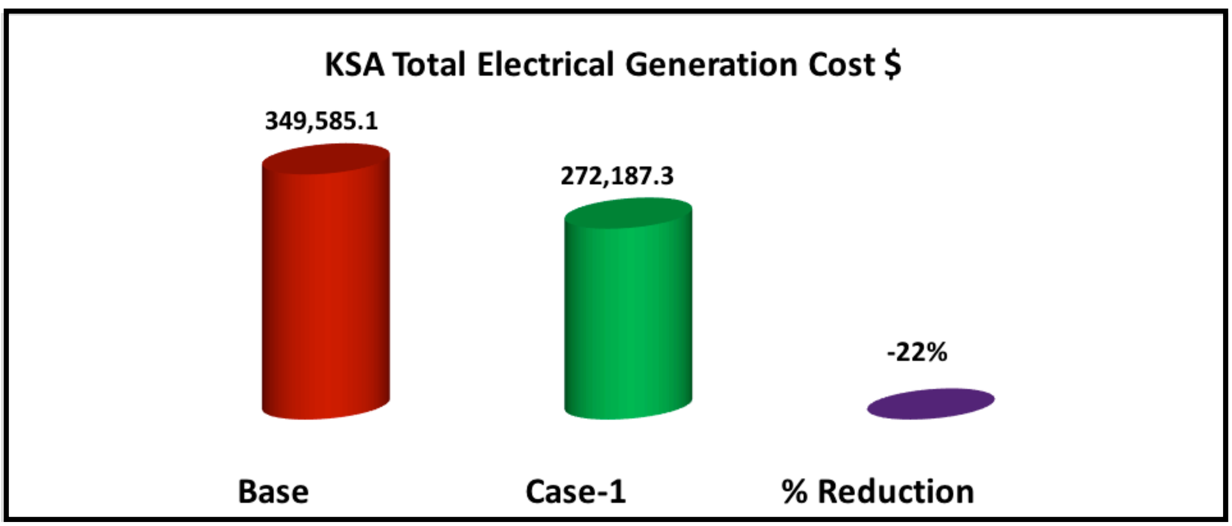

Figure. 5: Base case vs. optimized case senario total generation cost

The base case benchmarked to the optimal case scenario fuel mix is shown in Figure 6. The diesel consumption was reduce to zero in the optimal case scenario as it is the most expensive fuel among the fuel mix. Also, the Arab Light crude (ALC), which is the second highest fuel with regard to cost among the fuel mix was reduced by 91%.

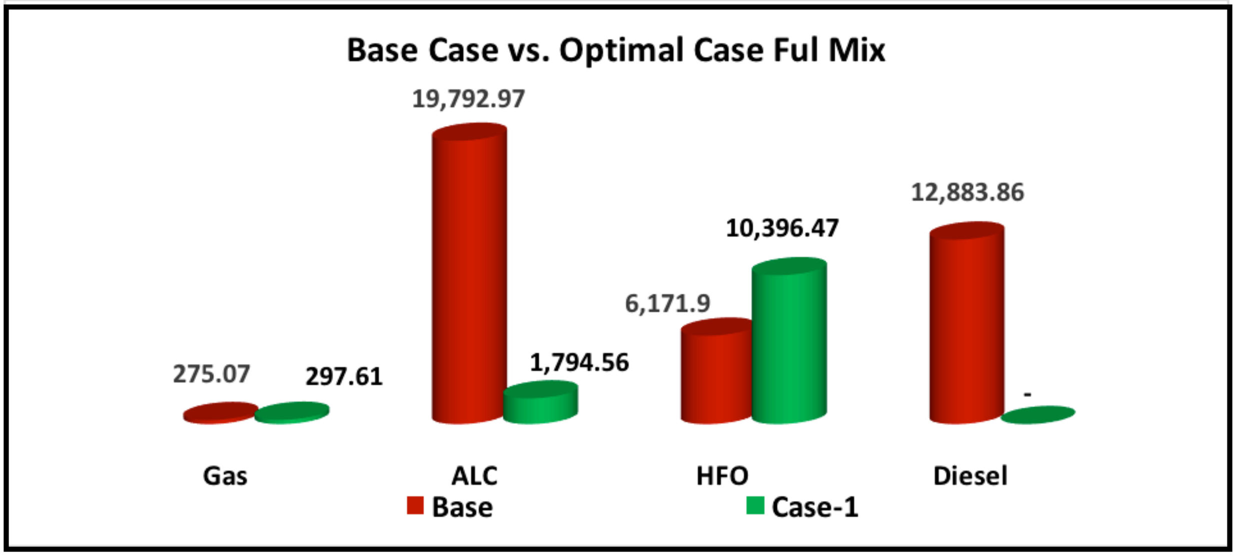

Figure. 6: Base case vs. optimized case senario fuel mix

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References

[1] Y. Zeng and Yanguang Sun, “Comparison of multiobjective particle swarm optimization and evolutionary algorithm for optimal reactive power dispatch problem,” IEEE Congress on Evolutionary Computation (CEC), Beijing, China, pp. 258–265, July 6-11, 2014.

[2] A. A. El-Fergany, “Optimal capacitor allocations using evolutionary algorithms,” IET Generation, Transmission & Distribution, vol. 7, Iss.6, pp. 593–601, 2013.

[3] M. T. Al-Hajri, M. Abido and M. K. Darwish, “Multiobjective Power Loss Optimization Versus System Stability Assessment for Hydrocarbon Industrial Plant Using Differential Evolution Algorithm”, The Eighth International Conference on Future Computational Technologies and Applications, March 20-24, 2016, Rome, Italy.

[4] S. Das and P. N. Suganthan “Differential Evolution: A Survey of the State-of-the-Art”, IEEE Transactions on Evolutionary Computation, Volume 15, Issue.1, pp. 4 – 31, 22 February 2011.

[5] K. P. Wong and ZhaoYang Dong, “Differential Evolution, an Alternative Approach to Evolutionary Algorithm” , Proceedings of the 13th International Conference on Intelligent Systems Application to Power Systems, Arlington, VA, Nov. 6-10, pp. 73 – 83, 2005.

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