Real Power Loss Optimization for a Hydrocarbon Industrial Plant Using Genetic Algorithm and Differential Evolution Algorithm

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***Abstract*- In this paper, a techno-economic assessment of a real life hydrocarbon facility electrical system real power loss optimization is addressed. This optimization was attained by using the Genetic Algorithm (GA) and the Differential Evolution Algorithm (DEA). The study is the first of its kind as none of the previous studies were conducted in the context of a real life hydrocarbon facility's electrical system. The hydrocarbon facility's electrical system examined in the study consisted of 275 buses, two gas turbine generators, two steam turbine generators, and large synchronous motors, with both rotational and static loads. For the real life hydrocarbon facility, the performance of the GA and the DEA were benchmarked in the course of optimizing the subject objective. The problem was articulated as a constrained nonlinear problem. The constraints were all real values reflecting the system equipment and components' limitations. The consequences obtained from the study showed the efficiency and prospects of the proposed algorithms in solving the described optimization case. Also presented in this study is the annual fuel cost avoidance.**

Keywords-genetic algorithm; differential evolution algorithm; power loss optimization; hydrocarbon facility; millions of standard cubical feet of gas (MMscf).

I. INTRODUCTION

Most of the oil exporting developing countries are facing a challenge associated with the increasing demand for domestic electrical energy. This increase has reached such an alarming level that it mandates action from the governments of the subject countries. For example, in the Kingdom of Saudi Arabia, the average annual increase in electricity demand is 7.4% [1].

In fact, in these countries, a high percentage of electric generation comes from low efficiency power generation plants, such as the simple cycle steam turbine. This complicates the issue, creating an urgent requirement for the utilization of more efficient plants coupled with a reduction in loss in the transmission and distribution system. In Saudi Arabia, the distribution of plant capacity for electricity generation by technology illustrates that low efficiency simple cycle steam turbine generators make up 32% of the utility company's generation fleet, while the most efficient combined cycle generators are around 13.8% of the whole fleet [2].

The aforementioned challenges gave impetus to the idea of studying the potential to use intelligent algorithms in optimizing real hydrocarbon facility power loss. The study used the real values of the system parameters and practical constraints, which escalated the challenges in finding a global solution.

This paper considers an existing real life hydrocarbon central processing facility electrical power system model for assessing the potential of system real power loss minimization using the Genetic Algorithm (GA) and the Differential Evolution Algorithm (DEA) for two generation modes. In Section 2, the problem will be formulated as optimization problem with equality and inequality constrains. In Section 3, the GA and DEA will be employed to solve this problem. In Section 4, the paper study scenarios will be developed. Finally, in Section 5 techno-economic analysis of the results and discussion will be presented.

II. 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.

A. Problem Objective Function

The objective to be achieved is the minimization of the real power loss J_1 (P_{Loss}) in the transmission and distribution lines. This objective function can be expressed in terms of the power follow loss between two buses *i* and *j* as follows:

$$J_I = P_{Loss} = \sum_{k=1}^{nl} g_k \, [\, V_i^2 + V_j^2 - 2\, V_i V_j \cos(\delta_i - \delta_i)] \quad (1)$$

Where *nl* is the number of transmission and distribution lines; g_k is the conductance of the k^{th} line, $V_i \angle\delta_i$ and $V_j \angle\delta_j$ are the voltage at end buses *i* and *j* of the k^{th} line, respectively [3] [4].

B. Problem Equality and Inequality Constrains

The system constrains are divided into two categories: equality constrains and inequality constrains [3][5]. Details are as follows:

B.1 Equality Constrains

These constrains represent the power load flow equations. The balance between the active power injected P_{Gi}, the active power demand P_{Di} and the active power loss P_{li} at any bus i is equal to zero. The same balance applies for the reactive power Q_{Gi}, Q_{Di} , and Q_{li}. These balances are presented as follows:

$$P_{Gi} - P_{Di} - P_{li} = 0 \tag{2}$$

$$Q_{Gi} - Q_{Di} - Q_{li} = 0 \tag{3}$$

The above equations can be detailed as follows:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} \boldsymbol{V_j} \left[G_{ij} cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j) \right] = 0 \tag{4}$$

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

where i = 1,2,…,NB;NB is the number of buses; P_G and Q_G are the generator real and reactive power, respectively; P_D and Q_D are the load real and reactive power, respectively; G_{ij} and B_{ij} are the conductance and susceptance between bus i and bus j, respectively.

B.2 Inequality Constrains

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

a. Generator and synchronous motor voltages; V_G and V_{Synch}; their reactive power outputs; Q_G and Q_{Synch}.
b. The transformers taps.
c. The load buses voltages V_L.

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

Minimize $\boldsymbol{J_1}$
Subject to:

$$g(x,u) = 0 \tag{6}$$

$$|h(x,u)| \leq 0 \tag{7}$$

Where:

x: is the vector of dependent variables consisting of load bus voltage V_L, generator reactive power outputs Q_G and the synchronous motors reactive Power Q_{Synch}. As a result, x can be expressed as

$$x^T = [V_{L1}..V_{LNL}, Q_{Gi}\ldots Q_{GNG}, Q_{Synchi}\ldots Q_{SynchNSynch}] \tag{6}$$

u: is the vector of control variables consisting of generator voltages V_G, transformer tap settings T, and synchronous motors voltage V_{Synch}. As a result, u can be expressed as

$$u^T = [V_{G1}..V_{GNL}, T_1\ldots T_{NT}, V_{Synch1}..V_{SynchNL}] \tag{8}$$

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

All the constraints posted in Table 1 are real values based on the system and equipment real data.

TABLE 1
SYSTEM INEQUALITY CONSTRAINS

Description	Lower Limit	Upper Limit
GTG Terminal Voltage (V_{GTG})	90%	105%
STG Terminal Voltage (V_{STG})	90%	105%
GTG Reactive Power (Q_{GTG}) Limit	-62.123 MVAR	95.72 MVAR
STG-1 Reactive Power (Q_{STG}) Limit	-22.4 MVAR	20.92 MVAR
STG-2 Reactive Power (Q_{STG}) Limit	-41.9 MVAR	53.837 MVAR
Captive Synch. Motors Terminal Voltage	90%	105%
Synch. Motors Terminal Voltage (V_{Sychn})	90%	105%
Causeway downstream Buses Voltage	95%	105%
All Load Buses Voltage	90%	105%
Main Transformer Taps	+16 (+10%)	-16 (-10%)
Generators Step-Up Transformer Taps	+8 (+10%)	-8 (-10%)

III. THE PROPOSED APPROACH

A. Generic Algorithm (GA) Implementation

The implementation of the GA technique can be summarized in the following steps [6]-[12]:

1) Generate initial populations of chromosomes; each chromosome consists of genes and each of these genes represents either transformer tap settings, synchronous motors voltages or the generators voltages values.
2) Assign fitness to each chromosomes, as follows:
   a. Use the Newton-Raphson method to calculate the real power losses for each population [8].
   b. Identify if the voltage constrains are satisfied.
   c. Identify if the synchronous machines (generators and motors) capacity limitations are met.
   d. Assign fitness values to the populations that meet all the constrains; the population best power loss value ($\boldsymbol{J_1}$).
3) Identify the best population with its associated chromosomes that has the best objective function value and store it.
4) Identify the chromosomes parents that will go to the mating pool for producing the next generation via the random selection method. This method works by generating two random integer numbers (each represents a chromosome). Then, these two randomly selected chromosomes fitness values are compared and the one with the better fitness value will go into the mating pool. This randomly selected chromosomes mechanism will be repeated until the population in the mating pool equals to the initial chromosomes population [13].
5) Perform genes crossover for the mating pool parents via the simple crossover method [13]. In this method, the offspring chromosomes are generated by establishing a vertical crossover position for parent's chromosomes and then crossover their genes.

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6) Perform gene mutation for the mating pool parents after they have been crossed over; the random mutation method was implemented [13]. In this method, the offspring chromosomes genes are mutated to new ones randomly from the genes domain.
7) Go to Step #2 and repeat the above steps with the new populations generated from the original chromosome parents after being crossed over and mutated.
8) Each time, identify the best population and compare its fitness value with the stored one; if it is better (meeting the objective function), replace the best chromosomes with the new ones.
9) The loop of generation is repeated until the best population with its associated chromosomes, in terms of minimum real power loss, is identified or the maximum number of generations is met. The flow chart of the proposed approach is shown in Fig. 1.

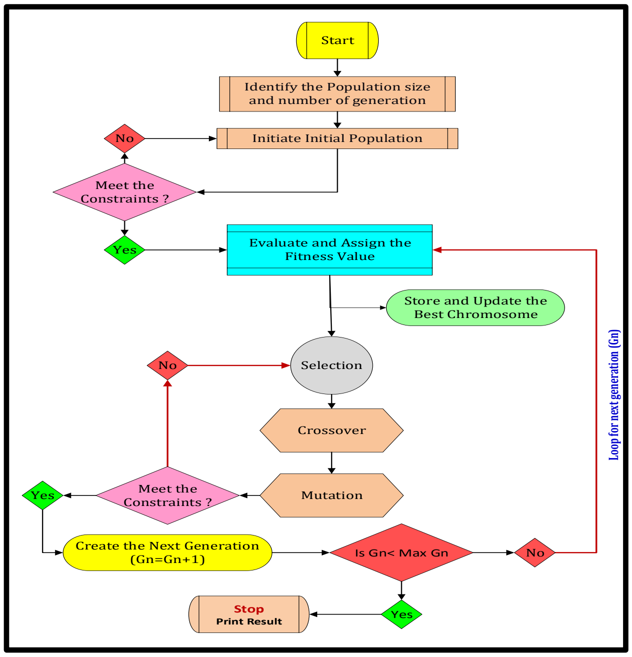

Figure 1. The GA algorithm evolution process flowchart

B. Differential Evolution Algorithm (DEA) Implementation

DEA utilizes special differential operators in creating the offspring individuals from the parent individuals' population in place of the classical crossover and mutation operators used in the GA. In DEA, there are two control parameters, which are the mutation constant F and the crossover constant C. Different from the GA, in the DEA the mutations are performed before the crossover and the selection is taken place after both the mutation and the crossover. DEA's first three evolutionary process steps are similar to the GA ones. [14]-[18]. The remaining steps are as described below:

4) In the DEA, mutations are performed using the DE/rand/1 mutation technique [17]. V*i* (t) - the mutated vector, is created for each population member X_i (t) set by randomly selecting three individuals' x_{r1}, x_{r2} and x_{r3} 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:

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

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 Fig. 2.

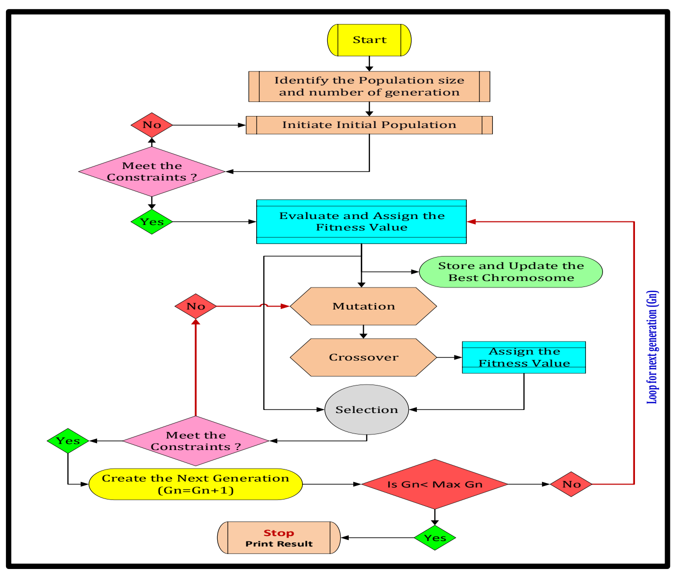

Figure. 2: DEA in single-objective mode evolutionary process chart

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IV. STUDY SCENARIOS

In this paper, three scenarios were studied: the base case scenario- business as usual (BAU), the optimal case scenario when all generators are online, and the optimal case scenario when two generators are offline. In the optimal cases, the best system parameters (chromosomes) that meet the minimum objective function (J1) are obtained.

A. Base Case Scenario

The BAU scenario was simulated to be benchmarked with the two optimal scenarios. Following are some of the normal system operation mode parameters:

1) The utility bus and generators terminal buses were set at unity p.u. voltage.
2) All the synchronous motors were set to operate very close to the unity power factor.
3) All downstream distribution transformers and the captive synchronous motors transformers; off-load tap changers; were put on the neutral tap.
4) The causeway substations main transformers taps were raised to meet the very conservative voltage constrains at these substations downstream buses; ≥ 0.95 p.u. Refer to Table 2 below.

TABLE 2
THE SELECTED FEASIBLE TRANSFORMERS TAPS VALUE

Substation Number	Transformer Tap
Causeway Substation#1	+3 (1.019 p.u.)
Causeway Substation#2	Neutral (1.0 p.u.)
Causeway Substation#3	+3 (1.019 p.u.)
Main Substation Transformers	+1 (1.006 p.u.)

B. Optimal Case Scenario with All Generators Online

In this scenario, all the generators were assumed to be online. The initial 100 populations of feasible chromosomes (individuals), which meet both the buses voltage and synchronous machine reactive power constrains were identified. The feasible populations with their associated chromosomes were subject to the GA and DEA evolutionary process of 100 generations guided by the objective function J_1. The GA process was set with 90% crossover probability and 10% mutation probability. In the DEA case, the mutation F constant was set equal to 0.5 (50%) and the CR is set equal to 0.9 (90%). The system parameters and the objective function value associated with the optimal solution of this scenario were identified.

C. Optimal Case Scenario with Two Generators Offline

In this scenario, two generators (one gas turbine generator and one steam turbine generator) were assumed to be offline. All others parameters are identical to the optimal case scenario with all generators are online.

V. RESULTS ANALYSIS AND DISCUSSIONS

The results from the three scenarios, base case, when all generators online and with two generators offline will be analysed in two categories: the system parameters analysis and the economic analysis.

A. System Parameters Analysis

The hydrocarbon facility simplified electrical system model, which is studied in this paper, is shown in Fig. 3. The evolution of the objective function (J_1) values over the GA and DEA evolution process is captured in Fig. 4. In the all generators online scenario the GA converted to its optimal J_1 value of 1.892 MW after 53 generations while the DEA converted to better J_1 value of 1.885 MW but after 78 generations. So, DEA converted to a better J_1 value but after a higher number of generations. In the scenario with two generators offline, DEA converted to again better J_1 value of 2.926 MW at generation 72 while the GA converted to its optimal J_1 value of 2.933 MW after 91 generation. In this scenario, DEA produced a better J_1 value and within a lower number of generations compared to the GA. The evolution process for both the GA and the DEA were repeated many times to confirm the obtained results.

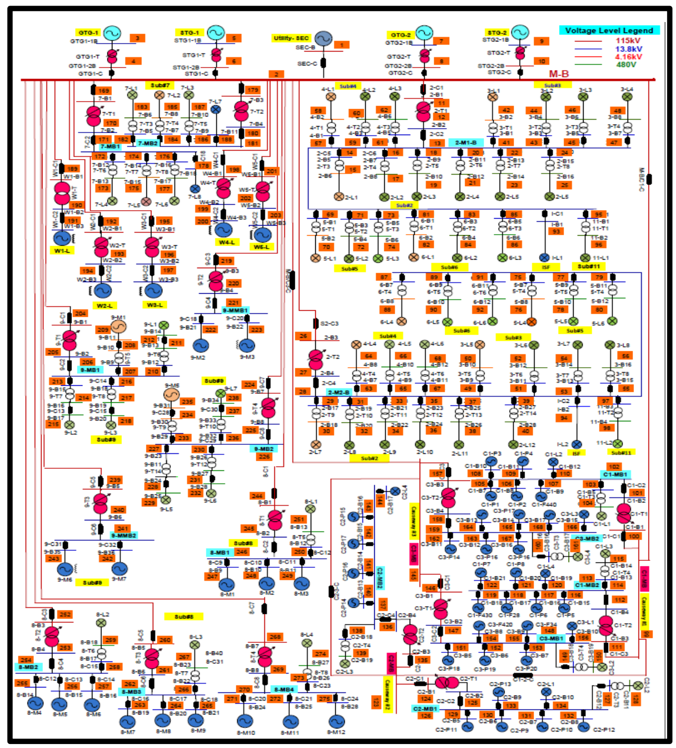

Figure 3. Simplified electrical system of the hydrocarbon processing facilty

In Table 3, a comparison of the objective functions' values are posted for the three studied scenarios. The DEA performs better than the GA for the all generators' online scenario. J_1 was reduced by 11.67% when compared with the BAU values. Also, DEA produced better objectives' values than GA for the two generators' offline mode.

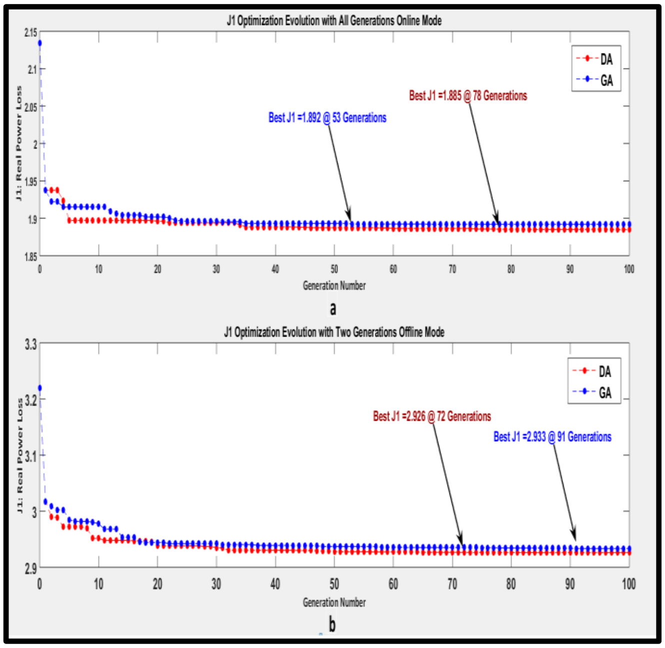

Figure 4. J_1 value convergent for the two generation scenarios

TABLE 3
THE J_1 VALUES FOR THE STUDIED THREE SCENARIOS

Generation Mode	Case #	J_1 Value	$\Delta J_1 \%$
All online	BAU	2.134	0.00
Two offline	BAU	3.219	0.00
All online	GA	1.892	-11.34%
All online	DEA	1.885	-11.67%
Two offline	GA	2.933	-8.89%6
Two offline	DEA	2.926	-9.10%

B. Economic Analysis

The annual cost due to the system real power loss calculated based on natural gas cost of $3.5 per MM is demonstrated in Table 4. In the all generators online scenario, DEA produce better real power loss cost $561,782 which is $74,200 less than the BAU power loss cost and $2,076 less when benchmarked with GA. Also, DEA produce better real power loss of $872,124 which is $87,361 less than the BAU power loss cost and $2,161 less when compared with GA real power loss cost value.

TABLE 4
ECONOMIC ANALYSIS FOR THE STUDIED THREE SCENARIOS

Generation Mode	Case#	Real Power Loss Cost
All online	BAU	(635,982.30)
Two offline	BAU	(959,485.76)
All online	GA	(563,858.10)
All online	DEA	(561,782.11)
Two offline	GA	(874,285.01)
Two offline	DEA	(872,124.64)

VI. CONCLUSION AND FUTURE WORK

This paper presented the potential of minimizing the real system's power loss for a real-life hydrocarbon facility using the GA and DEA approach. Three scenarios were considered, the base case scenario and two generation scenarios. The technical and economic advantages of the optimal scenarios versus the base case scenario were highlighted in this paper. Also, the superiority of applying DEA to search for the optimal value of the objective function over the GA was highlighted. Future study may need to address the problem as a multi-objective problem considering the grid connection power factor as a second objective which competes with the real power loss minimization objective.

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