Multiobjective Power Loss Optimization Versus System Stability Assessment for Hydrocarbon Industrial Plant Using Differential Evolution Algorithm

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***Abstract*- In this paper, a differential evolution algorithm (DEA) is considered for formulating nonlinear constrained multiobjective problem where electrical system real power loss and voltage stability index are optimized concurrently for a real hydrocarbon industrial plant. The subject plant electrical system consists of 275 buses, two gas turbine generators, two steam turbine generators, large synchronous motors, and other rotational and static loads. Truncation mechanism is used to manage the pareto-optimal solution set size. The best compromise solution is extracted using fuzzy set theory. The DEA performance for different population sizes and generation number cases will be demonstrated. The results exhibited the capabilities of the proposed approach in producing optimized pareto-optimal solutions for the subject multiobjective problem. The byproduct annual cost avoidance potential due to real power loss optimization for the studied cases will be demonstrated.**

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

I. INTRODUCTION

Due to the exponential increase of the electrical power demand and the average low generation efficiency in most of the developing countries, the issue of reducing the electrical power system loss while maintaining the system stability has received more attention. For example, in Saudi Arabia, the annual average peak electric demand increase is around 7.4% [1]. As of 2013, the distribution of plant capacity for electricity generation in Saudi Arabia, by technology is shown in Figure 1. The low efficient simple cycle steam turbine generation is making 32% of Saudi Arabia utility company generation fleet while the most efficient combined cycle is around 13.8% of the whole fleet [2]. These inspired most of the developing countries to unleash national initiatives to optimize electrical usage and reduce system loss. The subject issue can be addressed by adjusting transformer taps and generators and synchronous motors buses voltages.

Heuristic methods are very powerful in addressing the electricals system loss optimization by searching the solution space for the optimal solutions. Many intelligent algorithms were implemented to identify the pareto-optimal solution set for the subject. The DEA in most cases demonstrates superior

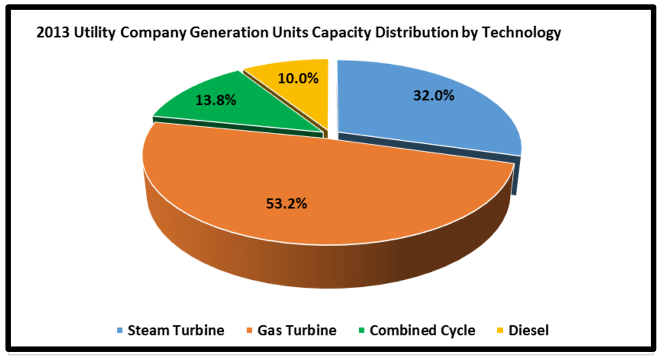

Figure 1. Saudi Arabia generation units fleet distribution by technology

over other algorithms such as the genetic algorithm [3]-[6]. Most of the previous studies in the literature used virtual IEEE system models to address the power loss and system stability multiobjective optimization problem or other problems [7]-[9]. A truncation technique is implemented with the DEA to manage the size of the Pareto-optimal set solution [9]. The fuzzy logic is the most common technique in extracting the best compromise solution out of the pareto-optimal solution set [7][9].

This paper considers an existing real life hydrocarbon central processing facility electrical power system model for assessing the potential of DEA in optimizing two competing objectives simultaneously: power system loss and system stability index improvement. In Section 2 of the paper, the problem will be formulated as a multiobjective optimization problem with equality and inequality constraints. In Section 3, the multiobjective optimization process will be illustrated. In Section 4, the DEA approach will be addressed. In Section 5, the paper study cases will be developed. Finally, in Section 6 the technical and economic analysis of the studied cases results will be presented.

II. PROBLEM FORMULATION

The problem formulation consists of five parts: the development of the objective functions, the calculation of all load buses stability index (L-Index), the identification of the system electrical constraints to be met - equality and inequality constraints - and the illustration of the fuzzy logic and the truncation technique.

A. Problem Objective Functions

In this paper, two competing objective functions will be addressed as follows:

A.1 System Loss Objective Function

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

$$J_1 = P_{Loss} = \sum_{k=1}^{nl} g_k \,[\, V_i^2 + V_j^2 - 2\, V_i V_j \cos(\delta_i - \delta_j)] \tag{1}$$

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 [7] [9].

The objective is to minimize P_{loss}, that is,
J_1= Minimize (P_{loss}) (2)

A.2 Voltage Stability Index (L_{max})

The L indicator varies in the range between 0 (the no load case) and 1, which corresponds to voltage collapse. This indicator uses the bus voltage and network information provided by the power flow program to measure the stability of the system. The L indicator can be calculated as given in [10]. For a multi-node system

$$I_{bus} = Y_{bus} \times V_{bus} \tag{3}$$

By segregating the load buses (PQ) from generator buses (PV), (3) can be written as:

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = \begin{bmatrix} Y_1 & Y_2 \\ Y_3 & Y_4 \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix} \tag{4}$$

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} H_1 & H_2 \\ H_3 & H_4 \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \tag{5}$$

where
V_L , I_L *are load buses voltages and currents*
V_G , I_G *are Generator buses voltages and currents*
H_1 ,H_2 ,H_3 ,H_4 *are submatrices generated from* Y_{bus} *Partial Inversion*
Z_{LL} ,F_{LG} , K_{GL} ,Y_{GG} *are submatrices of H-matrix*

Therefore, a local indicator L_j can be worked out for each node j similar to the line model

$$L_j = \left| 1 - \frac{\sum_{i \in \alpha G} F_{ji} V_i}{V_j} \right| \tag{6}$$

For a stable situation, the condition $L_j \le 1$ must not be violated for any of the nodes j. Therefore, a global indicator L describing the stability of the whole system is given by:

$$L_{max} = \mathrm{MAX}_{j \in \alpha L} \left| 1 - \frac{\sum_{i \in \alpha G} F_{ji} V_i}{V_j} \right| \tag{7}$$

where α_L is the set of load buses and α_G is the set of generator buses.

The objective is to minimize L_{max}, that is,
J_2= Minimize (L_{max}) (8)

Combining the objectives functions and these constraints, the problem can be mathematically formulated as a nonlinear constrained single objective optimization problem as follows:

Minimize J_1 and J_2
Subject to:

$$g(x,u) = 0 \tag{9}$$
$$|h(x,u)| \le 0 \tag{10}$$

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

$$x^T = [V_{L1}..V_{LNL}, Q_{Gi}\ldots Q_{GNG}, Q_{Synchi}\ldots Q_{SynchNSynch}] \tag{11}$$

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

$$u^T = [V_{G1}..V_{GNL}, T_1\ldots T_{NT}, V_{Synch1}..V_{SynchNL}] \tag{12}$$

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

B. Problem Equality and Inequality Constraints

The system constraints are divided into two categories: equality constraints and inequality constraints [6][7]. Details are as follows:

B.1 Equality Constraints

These constraints 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 apply for the reactive power Q_{Gi}, Q_{Di} , and Q_{li}. These balances are presented as follows:

$$P_{Gi} - P_{Di} - P_{li} = 0 \tag{13}$$

$$Q_{Gi} - Q_{Di} - Q_{li} = 0 \tag{14}$$

The above equations cane be detailed as follows:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} \boldsymbol{V_j} \, [\, G_{ij} cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] = 0 \qquad (15)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} \boldsymbol{V_j} \, [\, G_{ij} sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] = 0 \qquad (16)$$

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 Constraints

These constraints represent the system operating constraints posted in Table IV.

C. Fuzzy Logic for Selecting the Best Compromise Solution

Upon having the Pareto-optimal set of nondominated solution, the proposed approach presents one solution to the decision maker as the best compromise solution. Due to imprecise nature of the decision maker's judgment, the *i*-th objective function F_i is represented by a membership function μ_i defined as [7] [9].

$$\mu_i = \begin{cases} 1 & F_i \le F_i^{\min} \\ \dfrac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} & F_i^{\min} < F_i < F_i^{\max} \\ 0 & F_i \ge F_i^{\max} \end{cases} \qquad (17)$$

where $F_i^{\min}$ and $F_i^{\max}$ are the minimum and maximum value of the *i*-th objective function among all nondominated solutions, respectively.

For each nondominated solution *k*, the normalized membership function μ^k is calculated as

$$\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{N_{obj}} \mu_i^k} \qquad (18)$$

where *M* is the number of nondominated solutions. The best compromise solution is that having the maximum value of μ^k.

D. Pareto Set Reduction by Truncation

A minimum distance based algorithm [9] is employed to reduce the Pareto set to manageable size. At each iteration, an individual *i* is chosen for removal from the external pareto set P_{t+1}. The algorithm is illustrated in the following steps:

Step 1: find the nearest individuals A and B in the objective functions space.

Step 2: calculate the distance d_A and d_B of the next nearest individual from A and B in the objective function space respectively.

Step 3: Delete the individual with the smaller one between d_A and d_B.

III. MULTIOBJECTIVE OPTIMIZATION

In real life, there are problems that involve simultaneous optimization with no common thing in-between. Usually, these problems are competing multiobjective optimization which mandates developing a set of optimal solutions, instead of one optimal solution. The reason for the optimality of many solutions is that no one can be considered to be better than any other with respect to all objective functions. These optimal solutions are known as Pareto- optimal solutions set.

A universal multiobjective optimization problem consists of a number of objectives to be optimized simultaneously in association with a number of equality and inequality constraints. It can be formulated as follows:

$$Minimize \;\; f_i(x) \;\; i = 1,..., N_{obj} \qquad (19)$$

$$Subject\ to: \begin{cases} g_j(x) = 0 & j = 1,..., M \\ | h_k(x) | \le 0 & k = 1,..., K \end{cases} \;\; \text{Constraints} \qquad (20)$$

where f_i is the i^{th} objective functions, *x* is a decision vector that represents a solution, and N_{obj} is the number of objectives.

For a multiobjective optimization problem, any two solutions x^1 and x^2 can have one of two possibilities: one covers or dominates the other or none dominates the other. In a minimization problem, without loss of generality, a solution x^1 dominates x^2 if the following two conditions are satisfied:

$$1.\ \forall i \in \{1, 2, ..., N_{obj}\}: \ f_i(x^1) \le f_i(x^2) \qquad (21)$$

$$2.\ \exists j \in \{1, 2, ..., N_{obj}\}: \ f_j(x^1) < f_j(x^2) \qquad (22)$$

If any of the above conditions is violated, solution x^1 does not dominate the solution x^2. If x^1 dominates solution x^2, x^1 is called the nondominated solution. The solutions that are nondominated within the entire search space are denoted as *Pareto-optimal* and constitute the *Pareto-optimal set*.

IV. THE DEA APPROACH

The DEA evolution process are summarized in the following steps [11] [12]:

Step 1: Initialization

The population P_0 is generated with *K* size and an vacant annals (external) Pareto-optimal set $\overline{P}_0$ with $\overline{K}$ size.

Step 2: Updating of external pareto set

To bring the external pareto-optimal set up to date, the following steps are to be shadowed,

(a) Population non-dominated individuals are highlighted and reproduce to the external Pareto set.
(b) Look for set of external Pareto, designed for the non-dominated individuals.
(c) If condition ($\overline{P_{t+1}}$) $<\overline{K}$ is satisfied, keep the individuals with higher fitness values untial | $\overline{P_{t+1}}$| = $\overline{K}$ is satisfied.
(d) If ($\overline{P_{t+1}}$) $>\overline{K}$, truncation procedure is called which removes individuals from ($\overline{P_{t+1}}$) in anticipation of | $\overline{P_{t+1}}$| = $\overline{K}$.

Step 3: Assignment of fitness values

The fitness values of the individuals are calculated in the external Pareto set $\overline{P_t}$ and the population P_t as follows:

(a) St(*i*); strength value; is assigned to all individuals *i* inside the external pareto set $\overline{P_t}$ and the population P_t. St(*i*) signifies the unit, which *i* dominates and it is expressed as follow:

$$St(i) = |\{\, j, j \in P_t + \overline{P_t}, \wedge\, i \succ j \,\}| \tag{23}$$

Then, the raw fitness $R_w(i)$ with respect to an individual can be measured as follows:

$$R_w(i) = \sum_{j \in P_t + \overline{P}_t, j \succ i} St(j) \tag{24}$$

The raw fitness of an individual is obtained with respect to the strength of its dominators in the archive and population.

(b) The distances between an individual *i* and the entire *j* individuals, in the course of external and population sets and are enlisted. Then, the list is sorted in a cumulative manner, the distance to the m^{th} individual, consequently $m = \sqrt{\overline{K} + K}$ is represented as σ_i^m. Then, the density D(*i*) is calculated for each *i*

$$D(i) = \frac{1}{\sigma_i^m + 2} \tag{25}$$

The addition of integer 2 is made in the denominator to certify that the value of D (*i*) is larger than zero and is < 1. The fitness value *i* of an individual *is* expressed as follows*:*

$$F(i) = R_w(i) + D(i) \tag{26}$$

Step 4: Mutation

Different from the SPEA2 in which the individuals to be subjected to crossover and mutation are selected from the front pareto optimal set, in DEA the individuals are selected from the population. In the DEA, mutation is performed using the DE/rand/1 mutation technique. $V_i(t)$, 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 different between any two of the selected individuals. The resultant difference is added to the third selected individual. The mutation process can be written as:

$$V_{i,j}(t) = x_{r1,j}(t) + F \cdot [\, x_{r2,j}(t) - x_{r3,j}(t) \,] \tag{27}$$

The value of *F* is usually selected between 0.4 and 1.0; in this study F was set to be 0.5 (50%).

Step 5: Crossover

Perform the binomial crossover, which can be expressed as follow:

$$u_{i,j}(t) = \begin{cases} v_{i,j}(t) \; if \; rand\,(0,1) < CR \\ x_{i,j}\,(t) \qquad\qquad\qquad else \end{cases} \tag{28}$$

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

Step 6: Selection

The procedure for the selection is as follows:

$$x_i(t+1) = u_i(t) \quad \text{condition} \quad f(u_i(t)) \leq f(x_i(t)) \tag{29}$$

$$x_i(t+1) = x_i(t) \quad \text{condition} \quad f(x_i(t)) \leq f(u_i(t)) \tag{30}$$

where *f*( ) is the objective function to be minimized.

Step 7: Looping back/Termination

Look for the terminating criteria. If the criteria are not fulfilled, then generate new offspring population to previous one. If satisfied, apply the fuzzy set theory for the identification of the best compromise pareto set. Figure 2. demonstrates DEA evolutionary steps.

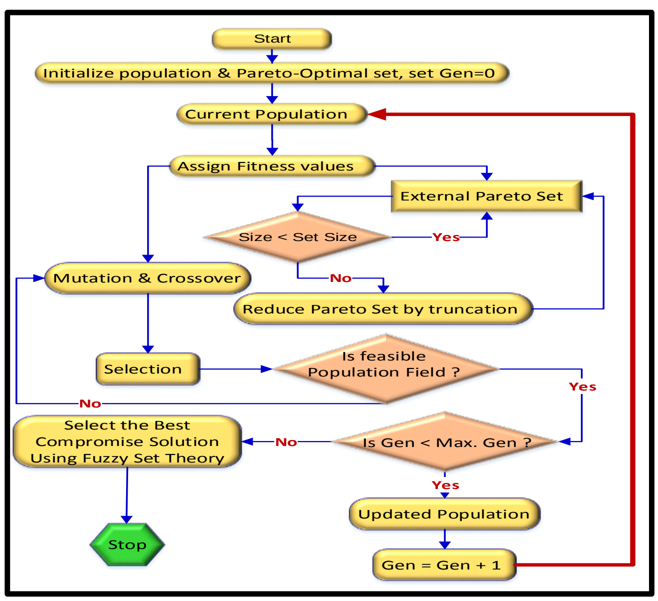

Figure 2. DEA evolutionary process chart

V. STUDY CASES

In this paper, three cases were studied. First, is the base case - business as usual (BAU). Second, the different number of generation with fix population size optimization case.

Third, the different population size with fix number of generation optimization case. In the two optimization cases, the best compromised values of the objective functions (J_1 and J_2) are obtained.

A. Base Case Scenario (Business as Usual)

The base case scenario (BAU) which is also called normal system operation mode was simulated to be benchmarked with the two optimal cases. 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 buses voltage constraints ($\geq$ 0.95p.u.) at these substations downstream buses as posted in Table IV. These main transformers'selected taps values are as per Table I below.

TABLE I
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. Different Generation Number with Fix Population Size Case

In this case, the crossover rate is fixed at 90%, the mutation rate is fixed at 50%, the population size was fixed at 100 individuals and the front pareto set population is fixed to be 50 individuals. Yet, the number of generations was varied to be 50, 100 and 150 respectively. The effect of different number of generations on the DEA performance compared to the BAU case is posted in Table II.

TABLE II
EFFECT OF GENERATION NUMBER ON THE DEA PERFORMANCE

Generation #	BAU J_1/J_2	Optimal J_1/J_2	Δ% J_1/J_2
50	2.13/0.075	1.90/0.06636	-10.8%/-11.5%
100	2.13/0.075	1.893/0.06640	-11.1%/-11.5%
150	2.13/0.075	1.897/0.06633	-10.9%/-11.6%

C. Different Population Size with Fix Generation Number Case

In this case, the number of generations is fixed at 50, the crossover rate is fixed at 90%, the mutation rate is fixed at 50% and the front pareto set population is fixed to be 50 individuals. Yet, the population size was varied to be 100, 200 and 300 correspondingly. Table III shows the effect of population size on the DEA performance compared to the BAU case. Population size of 200 produces better optimized value of J_1 while population size of 300 produces better optimized value of J_2.

TABLE III
EFFECT OF POPULATION SIZE ON THE DEA PERFORMANCE

Population Size	BAU J_1/J_2	Optimal J_1/J_2	Δ% J_1/J_2
100	2.13/0.075	1.902/0.06636	-10.8% /-11.5%
200	2.13/0.075	1.892/0.06640	-11.2% /-11.5%
300	2.13/0.075	1.91/0.06633	-10.3% /-11.6%

VI. RESULTS AND DISCUSSIONS

The results from the three studied cases will be analyzed 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 Figure 3.

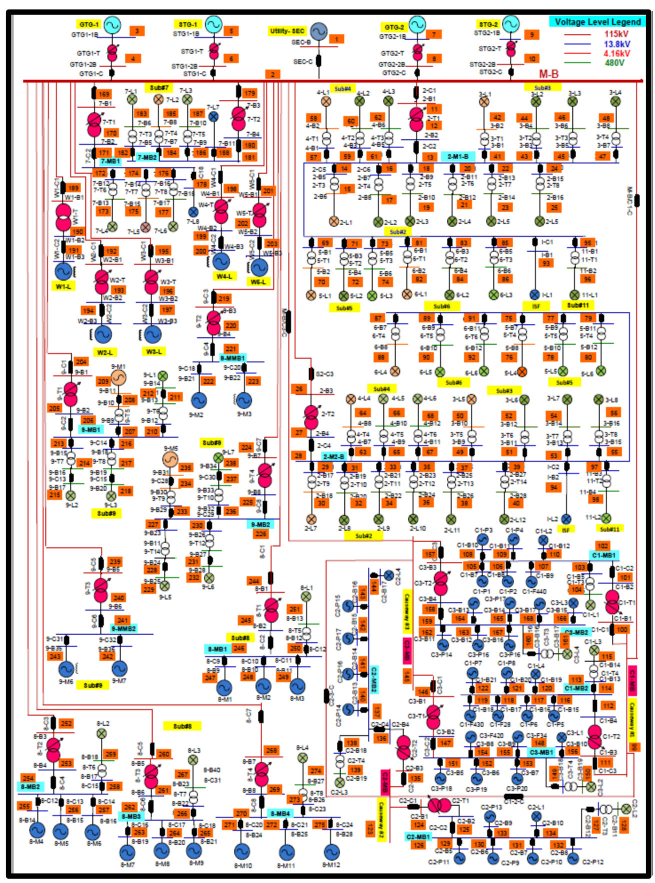

Figure 3. Simplified electrical system of the hydrocarbon facilty

The system inequality constraints are posted in Table IV. All these constraints are real system constraints for industrial electricals system. The real and reactive power limitations are manufactures actual limitations.

TABLE IV
SYSTEM INEQUALITY CONSTRAINTS

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	-62.12 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%)

The front pareto-optimal solution set for the first optimal studied case - different number of generation with fixed number of generation - is captured in Figure 4.

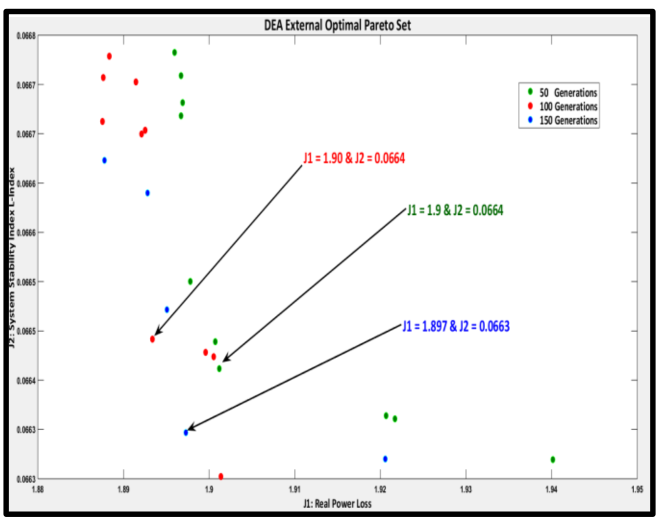

Figure 4. Pareto-optimal set solution for the first optimal case

The second optimal case - different population size - front pareto-optimal solution sets are shown in Figure 5. As shown in both figures none of the different population sizes or generation number produces very well distributed front pareto optimal set. A better distributed front pareto optimal set may be produced by trying higher population size or generation number. Yet, this will increase the evolution process. Massaging the crossover and mutation rate may also results in well distributed front pareto optimal set.

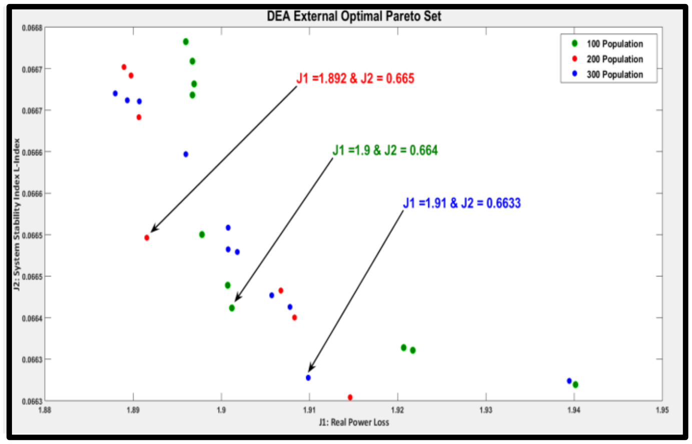

Figure 5. Pareto-optimal set solution for the second optimal case

B. Economic Analysis

The avoided annual cost due to the optimization of the system power loss is demonstrated in Figure 6 for the BAU and the two optimal cases. The annual cost avoidance based on natural gas cost of $3.5 per MMscf is around $69,507/year for the 150 generations with 100 population size scenario part of the first optimal case. It is $71,218/year for 200 population size with 50 generations scenario part of the second optimal case.

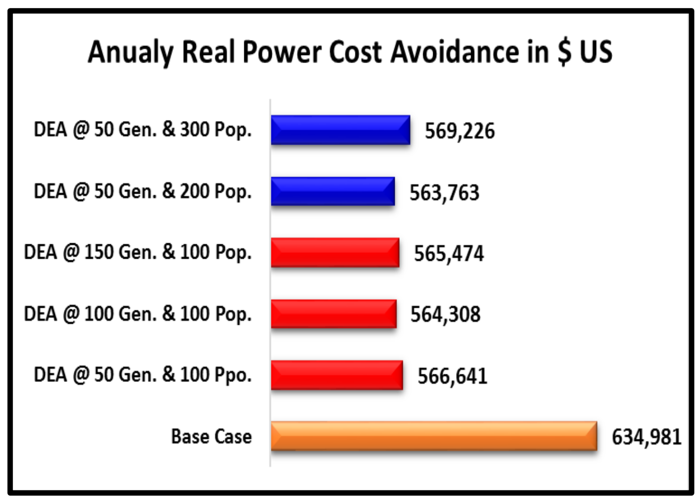

Figure 6. The avoided cost due to system power loss optimization

VII. CONCLUSION AND FUTURE WORK

This paper presented the potential of DEA in addressing the studied multiobjective problem for a real-life hydrocarbon facility. It was clearly demonstrated that increasing of generations number have better impact in producing better pareto-optimal set solution. Yet, many of the pareto-optimal solution set converged to the same J_1 and J_2 values. The annual avoided cost due to the power loss reduction was captured. Future study may need to address the effectiveness of different crossover and mutation rate percentage in the pareto-optimal solution set values and distribution. The use of different fix or dynamic mutation and crossover rate is a subject of future study considering the problem in hand.

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REFERENCES

[1] The Electricity Co-Generation Regulatory Authority (ECRA), "Annual Peak Load for the Kingdom", 2015, http://ecra.gov.sa/peak_load.aspx#.VOg-5I05BKA, [retrieved: January, 2016].

[2] 'Saudi Electrical Company 2013 annual report', https://www.se.com.sa/en-us/Lists/AnnualReports/Attachments/11/AnnualReport2013En.pdf [retrieved: January, 2016].

[3] K. Iba, "Reactive Power Optimization by Genetic Algorithm," IEEE Trans. on Power Systems, Vol. 9, No. 2, 1994, pp. 685-692.

[4] D. Gan, Z. Qu, and H. Cai, "Large-Scale VAR Optimization and Planning by Tabu Search," Electric Power Systems Research, 39, 1996, pp. 195-204.

[5] Y. T. Hsiao and H. D. Chiang, "Applying Network Window Schema and a Simulated Annealing Technique to Optimal VAR Planning in Large-Scale Power systems," Electric Power Systems Research, 22, 2000, pp. 1-8.

[6] P. Yonghong and L. Yi, "An Improved Genetic Algorithm for Reactive Power Optimization," Control Conference (CCC), 2011 30th Chinese, pp.2105-2109

[7] M. A. Abido, " Multiobjective Optimal VAR Dispatch Using Strength Pareto Evolutionary Algorithm," 2006 IEEE Congress on Evolutionary Computation, Vancouver, BC, Canada, July 16-21, 2006, pp. 730-736.

[8] D. Guan, Z. Cai and Z. Kong, "Reactive Power and Voltage Control Using Micro-Genetic Algorithm," International Conference on Mechatronics and Automation, Changchun, August 9-12, 2009, pp.5019-5024.

[9] Muhammad T. Al-Hajr and M. A. Abido, "Multiobjective optimal power flow using improved strength pareto evolutionary algorithm (SPEA2)," IEEE, 11th International Conference of Intelligent System Design and Application (ISDA), Cordoba, Spain, November 22-24, 2011, pp. 1–7.

[10] C. Belhadj and M. A. Abido, " An Optimized Fast Voltage Stability Indicator," IEEE Budapest Power Tech '99 Conference, Budapest, Hungary, August 29-September 2, 1999, BPT99-363-12 J, pp.79.

[11] M. Varadarajan and K. S. Swarup, "Solving multi-Objective optimal power flow using differential evolution," IET Generation, Transmission & Distribution, 2008, vol. 2, No. 5, pp. 720–730.

[12] Zhang Xuexia, Chen Weirong and P. N. Suganthan, "Optimal multi-objective reactive power dispatch considering static voltage stability based on dynamic multi-group self-adaptive differential evolution algorithm," IEEE International Conference on Intelligent system design and engineering application, 2012, , pp. 1448–1456.