Optimization and Layout of a Wind Farm Connected to a Power Distribution System

Hussein M. K. Al-Masri[1], *Member, IEEE*, Ahmad AbuElrub[2], *Member, IEEE* and Mehrdad Ehsani[3], *Life Fellow, IEEE*

[1]Department of Electrical Power Engineering, Yarmouk University, Jordan
[2]Department of Electrical Engineering, Jordan University of Science and Technology, Jordan
[3]Department of Electrical Engineering, Texas A&M University, College Station, USA

***Abstract* -- This paper presents a techno-economic and environmental investigation of a grid connected wind energy system in Jordan's desert as a case study application for an oil-importing country. The system is mathematically modeled in MATLAB based on the hourly instantaneous data of both wind speed and the 2016 load demand. Two artificial intelligence techniques of genetic algorithm (GA) and simulated annealing (SA) are used to get the global solution of the objective function, which is the cost of energy of retrofitted system. The carbon emissions and the cost of energy of the system are reduced by 58.39% and 18.74% respectively. So, harnessing wind power is a long-term solution and a viable alternative to the fossil fuels, because it is affordable and clean.**

***Index Terms*--Wind power plant, optimization, MATLAB, economic, environment, genetic algorithm, simulated annealing.**

I. INTRODUCTION

THE population of the world keeps growing and the electricity generated from fossil fuels continues to be economically infeasible and a significant cause of air pollution. So, it is essential that clean and sustainable sources of energy such as wind power should be explored. Wind energy installed capacity has had a significant increase recently. Global cumulative installed wind capacity has reached 486.749 GW in 2016 [1]. Moreover, related research activities which investigate wind energy integration to the electrical grid have flourished. In addition, in some remote areas far from load centers, a significant part of population does not have access to the utility grid. Therefore, off grid plants such as wind turbines and PV panels are installed, since the installation of huge electrical power plants centrally has a considerable cost. Sizing for wind energy plant should be carried out on the basis of wind potential evaluation in order to make an efficient design. Wind energy is extracted from wind turbines which are rotating machines that convert the kinetic energy stored in wind to an electrical energy. For projects which serve a large footprint area, wind turbines are grouped into a wind farm. Hence, the power production is maximized while minimizing the installation, operation and maintenance cost.

In the published literature, many techniques were used to perform planning and optimize a wind farm in order to maximize wind energy harvesting and minimize the system cost. In [2], the authors used genetic algorithm approach to find optimal wind turbine (WT) position. Actual long-term wind data were used along with genetic algorithm for wind farm layout optimization [3]. In [4-6], simulated annealing techniques were employed in order to find the optimal layout of a wind farm. An evolutionary algorithm was developed to solve a wind farm layout optimization problem as shown in [7]. In [8], the authors used the Binary Particle Swarm Optimization with Time-Varying Acceleration Coefficients to minimize the cost of extracted wind farm power subject to turbine position, average power generation and normalize cost of turbines amount. The authors of [9] developed a mixed-integer nonlinear discrete combinatorial optimization procedure to find the optimal planning of the wind farm. A multi-level extended pattern search algorithm is presented in [10] to find the optimal planning of wind farm and wind turbine sizing.

This paper studies the application of an on-grid wind energy system in Jordan's desert as a case study for a non-oil producing country. This is done by techno-economic and environmental investigation. Genetic Algorithm (*GA*) and Simulated Annealing (*SA*) will be used to find the optimal wind farm configuration connected to a distribution system in Jordan. The MATLAB optimization toolbox will be used to optimize the objective function, which is the cost of energy of the retrofitted system (COE_{RS}) and then compute the cost of wind energy (*CWE*).

II. ENTERPRISE SYSTEM AND DATA ANALYSIS

This paper investigates a wind farm installed in a location in Jordan's desert (29°39'47.6"N 35°02'46.1"E) that is 1.7 km away from Wadi Araba customs office, south of Jordan. It is going to be connected to a 33kV bus in the utility grid distribution system. Therefore, the data required for each component shown in Fig. 1 should be collected and well-prepared to mathematically model the entire system.

This includes the hourly wind speed, turbine data input and some technical inputs needed to compute the output of the wind farm. Further, the hourly load data is obtained. Finally, the technoeconomic inputs are needed to compute some economic indicators. Afterwards, the objective function of the COE_{RS} will be optimized using the GA and SA. Thereby, an appropriate layout of the optimal sized wind farm will be carried out. This will help compute many evaluation parameters of the proposed project such as the total current cost (TCC), wind energy fraction (WF), CWE and Carbon Dioxide Emissions (CDE).

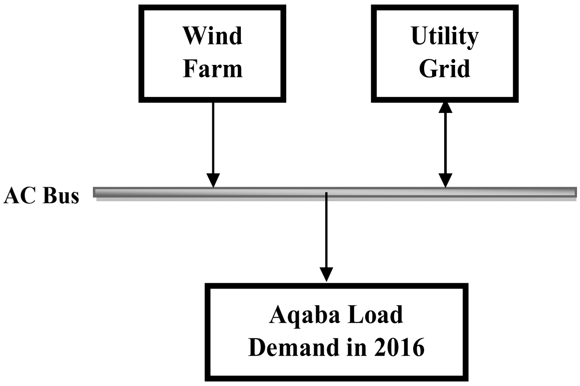

Fig. 1. Grid connected wind energy system

A. Wind Farm required data

The National Energy Research Center in Jordan is continuously conducting and preparing wind speed data in the promising sites at different heights [11]. This will help perform economic and environmental feasibility studies for the proposed sites. The monthly average wind speed data are obtained for the suggested location. It is considered as one of these high potential sites of wind energy. The altitude of this location above sea level (a.s.l) is 113 m. In order to generate hourly wind-speed data using only 12 monthly average values, the procedure in [12] is employed here in this paper which employs the Weibull distribution stochastic technique.

The Weibull distribution is widely used for modeling the stochastic behavior of wind speed. Using of Weibull probability distribution frequency (pdf) to represent the stochastic nature of wind speed is based on a comparison of actual wind speed profiles at different sites and wind speed profiles estimated using the Weibull pdf. The Weibull pdf is found to be valid for most wind speed profiles. Therefore, it has been used in this study to model the wind speed uncertainty over each time step [13]. The Weibull distribution pdf is given in (1).

$$f(v_w) = \left(\frac{k_i}{c_i}\right)\left(\frac{v_w}{c_i}\right)^{k_{i,j}-1} e^{-\left(\frac{v_w}{c_i}\right)^{k_i}} \quad (1)$$

Where c_i is Weibull scale parameter for time step i, and ki is Weibull shape parameter for time step i. Wind speed data are usually available in time series, in which each data point represents either an instantaneous sample of wind speed or an average wind speed over some time period. The estimation of Weibull parameters over each time step is done using the empirical method which is a special case of the moment method [14]. The Weibull pdf parameters k_i and c_i are calculated using (2) and (3).

$$k_i = \left(\frac{\sigma_{wi}}{\mu_{wi}}\right)^{-1.086} \quad (2)$$

$$c_i = \frac{\mu_{wi}}{\Gamma(1+\frac{1}{k_i})} \quad (3)$$

Where σ_{wi} is the standard deviation of wind speed data of time step *i*, μ_{wi} is the mean of wind speed data of time step *i*, and Γ is the gamma function.

Fig. 2 shows the hourly wind speed for the entire year. The annual average wind speed is 7.2498 m/s. As can be foreseen by investigating Fig. 2, most of the hourly wind speed values are around the annual average. This has also been noticed after building the histogram curve shown in Fig. 3. The annual average value is included in the bin number fifteen of the histogram diagram. This bin has edges of 7.2 and 7.5 m/s. The frequency of this range is 642, which is the highest value during the entire year.

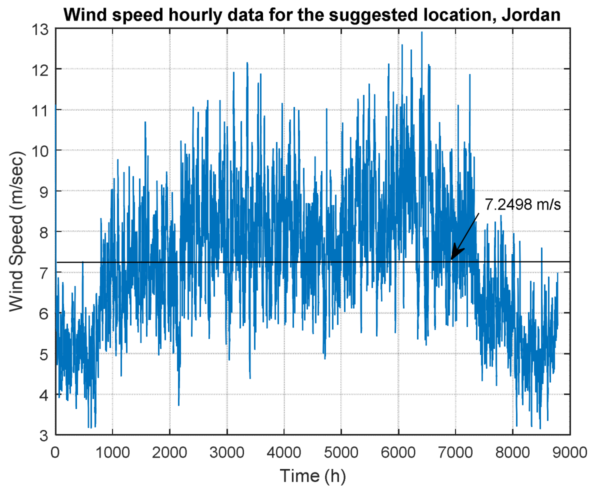

Fig. 2 Hourly wind speed data for the suggested location, Jordan

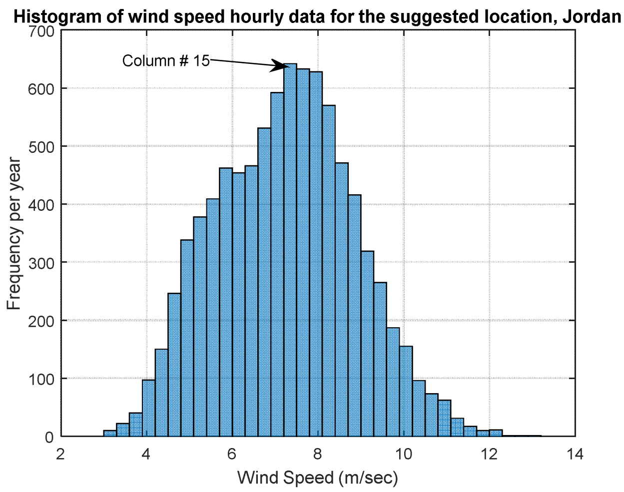

Fig. 3 Histogram of wind speed data for the suggested location, Jordan

On the other hand, Table I shows manufacturer datasheet of a V126-3.3 MW turbine. This Vestas wind turbine has been selected because it has light structural shell blades that will make sure to capture most of wind energy. It has been used before in Fujeij wind farm in Al Shobak, Governorate of Ma'an, Jordan. Fig. 4 shows the output power curve of this wind turbine once installed at the actual city elevation a.s.l. The rated wind speed increases as a result of the air density reduction, which causes the rated wind speed to be slightly different from the one shown in Table I.

TABLE I
DATASHEET OF A V126-3.3 MW WIND TURBINE

Parameter	*Value*
Rated power	3.3 MW
Cut-in wind speed	3 m/s
Rated wind speed	12 m/s
Cut-out wind speed	22.5 m/s
Rotor diameter	126 m
Swept Area	12,469.0 m²
Number of blades	3
Grid frequency	50 Hz
Hub height	137 m

The anemometer height is 45 m. However, the wind energy is generated at the hub height of the turbine. So, the wind speed hourly data shown in Fig. 2 are updated into the ones at the turbine hub height shown in Table I. So, the wind speed log profile law in (4) will be applied [15].

$$V_h = V_a\left(\frac{ln(H_h/r)}{ln(H_a/r)}\right) \tag{4}$$

Where: V_h and V_a are the wind speed values at the hub and the anemometer height respectively. H_h and H_a are the altitudes of the hub and the anemometer respectively. r is the surface roughness which is selected to be 3% based on the landscape of the selected location [16].

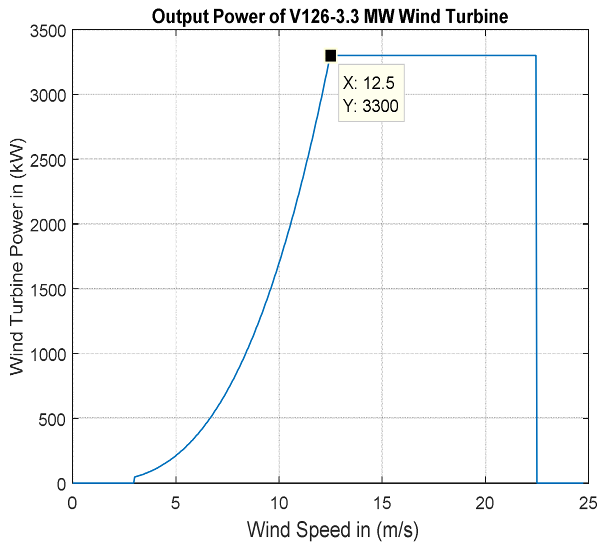

Fig. 4 Power curve of V126-3.3 MW turbine installed at 113m a.s.l

Wind turbines are usually spaced 5 to 9 times the rotor diameter (D) in the prevailing wind direction. Further, they are installed 3D to 5D in the direction perpendicular to the prevailing wind [17]. In this paper, the spacings between the wind farm columns and rows are selected according to the aforementioned rule of thumb to be 7D and 4D. In this case, the area of the wind farm (A_{farm}) can be calculated using (5).

$$A_{farm} = L \times W \tag{5}$$

Where: L and W are the length and the width of a rectangular wind farm respectively as shown in (6) and (7).

$$L = 4D(N_{col} - 1) + D \tag{6}$$

$$W = 7D(N_{row} - 1) + D \tag{7}$$

Where: N_{col} and N_{row} are the number of columns and rows of the windfarm respectively. Note that, any of these two variables can be expressed in terms of the other and the total number of turbines that will be optimized later using the artificial intelligence techniques. In this case, all of the possibilities of rows and columns will be considered. Then, the minimum and maximum required footprint will be calculated. An area limit of 20.6912 km², to install the wind farm, has been allocated using the Wikimapia Website [18].

B. Load demand required data

The hourly load demand data, for Aqaba Qasabah District, is considered and obtained from the Supervisory Control and Data Acquisition system of the National Control Center. It is considered as the backbone responsible for the control, planning and operation of the Jordan utility system.

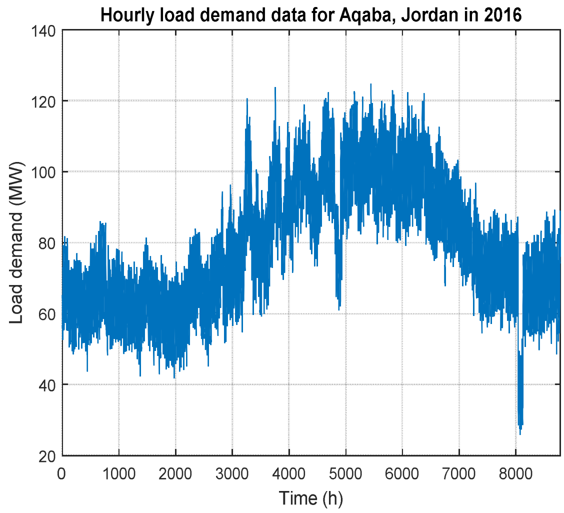

Fig. 5. Hourly load demand data for Aqaba, Jordan in 2016

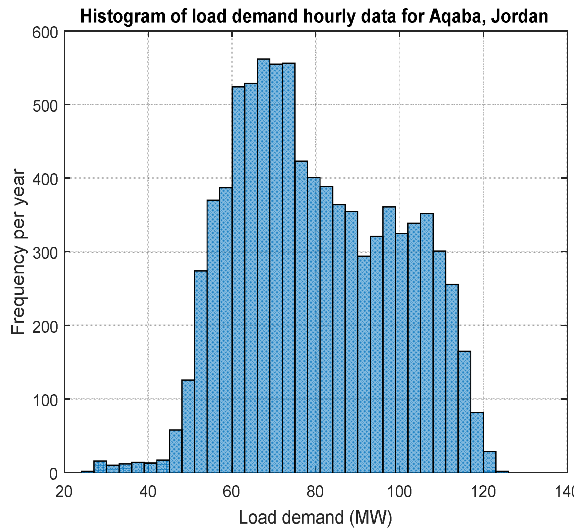

Fig. 6. Histogram of load demand hourly data for Aqaba, Jordan in 2016

As a matter of fact, the year of 2016 is a leap year including one more day (February 29th). So, it has 366 days i.e. 8784 hours. Fig. 5 shows the hourly load demand and Fig. 6 shows the corresponding histogram load diagram. The load factor, which is the ratio of average demand to the maximum demand within a given time period, is computed to be 64.28%.

III. System's Mathematical Modeling

A. Modeling of a wind turbine

The active power extracted from a wind turbine is computed as a fraction of the upstream wind power. As a matter of fact, the air density sweeping the turbine blades can be expressed in terms of the site elevation in meters as Equation (8) shows [19].

$$\rho = \rho_o - 1.194 \times 10^{-4} H \tag{8}$$

Where: H is the site altitude above sea level in meter. ρ_o is 1.225 kg/m^3, which is the air density at sea level (one atmospheric pressure of 14.7 psi and 60^{o}F) [19]. Considering the aforementioned information and assumptions, the WT real power is updated to a new form shown in (9).

$$P_{WT} = \frac{AC_p}{2}\left(\rho_o - 1.194 \times 10^{-4} H\right) v^3, \quad v_{ci} \le v \le v_{rated} \tag{9}$$

Where: A is area swept out by the blades in m^2. V is the wind velocity at the wind turbine hub height in m/s. V_{ci}, V_{rated} are the cut-in and rated wind speed respectively. C_p is the fraction of the upstream wind power captured by the WT rotor blades.

Practically, C_p is between 20% to 40% for turbines with more than two blades [19]. In this paper, C_p is assumed to have a constant value in the range between the cut-in and the rated wind speed values. It is computed using the rated values of turbine power and speed as well. Moreover, ρ is the Greek letter rho; that is equal to the density of air in kg/m^3.

B. Cost of energy of retrofitted system (COE_{RS})

Cost of energy of retrofitted system (COE_{RS}) is the cost of energy produced by the grid connected wind energy system in order to satisfy the load demand described in section II. It is computed by dividing the entire cost of the system to the entire energy absorbed by the load demand, see Equation 10.

$$COE_{RS} = \frac{Entire\ \ System\ \ Cost}{Entire\ \ Energy\ \ Absorbed} \tag{10}$$

Entire system cost is computed by firstly discounting wind farm cost components (capital, replacement, operation & maintenance and salvage costs) in the economic model to the present to compute total current cost (TCC) of the wind farm. This is done using discount factor (DF) shown in Equation 11 for each year (i). Then, TCC is multiplied with a capital recovery factor to get the total annualized cost so the cost of wind energy (CWE) can be computed as shown in Equations 12 and 13 [20]. Cost components, real interest rate, WT life time and project life time are shown in Table II [20]. Secondly, the entire system cost includes cost of the energy coming from utility grid. It was assumed that utility grid does not allow selling any energy back to the grid once the load demand is satisfied.

$$Discount\ factor = \frac{1}{(1+i)^t} \tag{11}$$

$$CWE = \frac{RF \times TCC}{Wind\ \ farm\ \ energy\ \ production} \tag{12}$$

$$\text{Recovery}\ factor = \frac{i(1+i)^t}{(1+i)^t - 1} \tag{13}$$

Further, the instantaneous wind speed hourly data in Fig. 2 is used to compute hourly output power of the wind farm using Equation 9. Then, the hourly energy at a one-hour time step is used to instantaneously satisfy the load demand shown in Fig. 5. This is done by hourly comparison feasibility process between the grid purchased energy and the energy produced by the wind farm. Also, the wind farm has been optimally sized based on the selected WT shown in Fig. 4.

COE_{RS} is the objective function to be optimized using the GA and SA. At first, load demand is satisfied by the wind farm energy system with (CWE) shown in Equation 12. Afterwards, utility grid can satisfy the rest of required energy till the load is completely satisfied with a cost that is equal to the grid purchase price shown in Table II.

TABLE II
ESTIMATED COST & LIFE TIME FOR SYSTEM'S COMPONENTS [20]

Parameter	Value
WT capital cost	2098$/kW
WT operation and maintenance cost	20.98$/kW/yr
WT Replacement cost	2098$/kW
Grid purchase price	0.134 $/kWh
Real interest rate (i)	5.88%
WT life time	20 years
Project life time	25 years

C. Wind energy fraction (WF)

The WF is the fraction of wind energy generated to the total system generation (14).

$$WF = \frac{Wind\ \ Energy\ \ Generated}{Total\ \ System\ \ Generation} \tag{14}$$

D. Carbon Dioxide Emissions (CDE)

CDE is a parameter measured in kiloton (kt) per year and it is used to indicate baseline emissions for the wind energy retrofitted system designed in this paper. In this case, a grid emission factor (kgCO_2/kWh) is needed, which is associated with each one kWh of electricity provided by the utility grid. In Jordan, it is equal to 0.583867 kgCO_2 per kWh [21].

IV. MATLAB Optimization Toolbox

After mathematically modeling the entire system shown in Fig. 1 and insert all the required technical and financial inputs, it is the time to optimize the objective function of the cost of energy of the grid connected wind energy system (COE_{RS}), which is expressed in Equation 10. The MATLAB optimization toolbox provides different techniques to find the minimum or maximum of an objective function while the constraints are satisfied. Two of these solvers are Genetic Algorithm (GA) and Simulated Annealing (SA). Those two artificial intelligence techniques are applied and tested to get the optimal value of the COE_{RS}.

A. Genetic Algorithm Optimization

GA is a heuristic method that examines an initial and random solution first, and then it explores many solutions in its search space till obtaining the optimal value of the fitness function. Those new solutions are generated continuously using genetic operators, i.e. crossover and mutation. In the crossover stage, a recombination of the current individuals is performed. Then, based on the fitness, new solutions (individuals) are reproduced. The mutation operator is very important to premature the convergence toward local optima [22]. The options in the GA solver toolbox are shown in Table III.

TABLE III
DEFAULT OPTIONS OF GA MATLAB TOOLBOX

Parameter	*Value*
Population size	200
Crossover fraction	0.9
Elite count	10
Generations	60
Time limit	15 hours
Tolerance function	10^{-6}
Stall time limit	10 hours
Stall generation limit	50
Lower bound	1
Lower bound	Inf
Number of variables	1

Afterwards, running the optimization has been terminated because the average change in the fitness value becomes less than (10^{-6}), which is the default tolerance value considered between the best and mean fitness. Fig. 7 shows how the GA converges toward the optimal value of the (COE_{RS}) by having the best fitness (dots) becomes exactly the same as the mean fitness (squares). At this point the number of wind turbines (WT_N) is equal to 23. The specifications of each turbine are given in Table I.

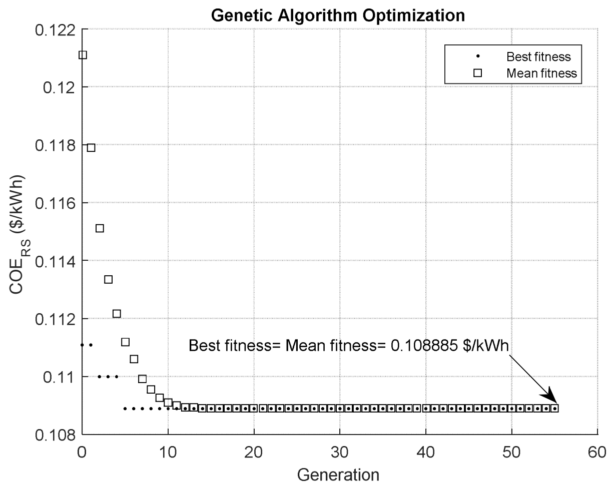

Fig. 7. GA to optimize COE_{RS}

As a matter of fact, the optimal value of the COE_{RS} is 18.74% less than the grid purchased price. This is an indication of the economic feasibility of the retrofitting system. Table IV shows detailed results of the optimized system. Note that, the minimum and maximum wind farm area are computed for 24 turbines in order to have possibilities for the number of columns and rows of the rectangular wind farm.

In 2015, the territorial CO_2 emissions per capita was 3.3729 tCO_2/person in Jordan [23]. Thereby, the CDE in Aqaba was 634.645 kt per year. Table IV shows that the CDE is 264.098 kt/year. As a result, 58.39% of carbon emissions will be reduced as a merit of the retrofitting wind energy on grid system. This is a decrease of 370.547 kt/year. Actually, this is an excellent indication for the environmental advantage of the proposed system to mitigate emissions from greenhouse gases.

TABLE IV
DETAILED RESULTS OF THE OPTIMIZED SYSTEM.

Parameter	*Value*
COE_{RS}	0.108885 \$/kWh
CDE	264.098 kt/year
CWE	0.064074 \$/kWh
WT_N	23
A_{farm}(min)	5.715360 km^2
A_{farm}(max)	7.429968 km^2
TCC	209.315 M\$
WF	35.8426%
Grid purchases cost	60.6117 M\$
Grid energy purchases	452.325809 MWh

B. Simulated Annealing Optimization

SA is another heuristic technique can be used to look for the global solution. It was proposed by Kirkpatrick, Gelatt, and Vecchi in 1983. The heating and cooling processes are the key behind understanding SA. It involves heating and then controls cooling of materials in order to increase the size of crystals and minimize their defects. At the beginning, the temperature is high. During the cooling process, while the temperature is gradually reduced, SA looks for the optimal solution in the search space [24]. The goal at this point is to apply the SA, as another optimization technique in order to verify if the solution obtained using the GA is robust and globally optimal.

The options in SA solver toolbox are shown in Table V. It has been noticed that SA algorithm stops after the average change in the objective function is below function tolerance shown in Table V.

TABLE V
DEFAULT OPTIONS OF SA MATLAB TOOLBOX

Parameter	*Value*
Max iterations	120
Time limit	Inf
Function tolerance	10^{-6}
Annealing function	Fast annealing
Initial temperature	100
Reannealing temperature	100
Tolerance function	10^{-6}
Stall iterations	500

Fig. 8 shows that the COE_{RS} optimal value is exactly the same as the value obtained before using the GA. Hence, all of the detailed results will be the same as given in Table III. This is an interesting outcome which proves that the solution obtained in this paper is global.

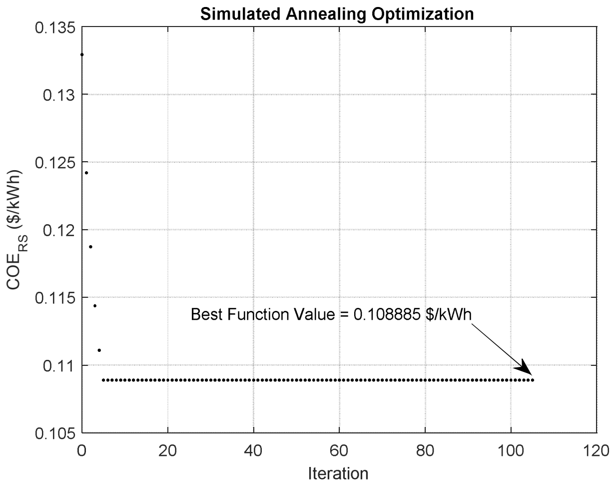

Fig. 8. SA to optimize COE_{RS}

V CONCLUSIONS

This paper presents a technical, feasible and environmental analysis for an on-grid wind farm. The system has been designed to satisfy Aqaba Qasabah District load demand in Jordan as a case study. A mathematical model for the output power form the wind farm was done, which takes into account many parameters such as: Wind speed hourly values for a year, which were modified using the logarithmic wind law. Also, the air density which is computed based on the actual city elevation. Further, an equation is developed to calculate the minimum and maximum footprint required to install wind farm. Moreover, hourly load demand is considered for a leap year. MATLAB is used to code the mathematical models presented. Further, GA and SA provided by MATLAB optimization toolbox are used to optimize the system. The COE_{RS} optimized value is 0.108885 $/kWh in both the GA and SA. The corresponding number of wind turbines, CWE, CDE, WF, TCC and grid purchases are 23, 0.064074 $/kWh, 264.098 kt/year, 35.8426%, $209.315M and $60.6117M respectively. In other words, COE_{RS} is 18.74% less than the utility grid purchased price. Furthermore, CO_2 emissions are mitigated by 58.39%. These are encouraging results for investors especially in the non-oil producing countries in harnessing wind power as a promising sustainable energy resource. It is a long-term solution to get economic and clean source of energy.

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