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Optimal Off-Grid Hybrid Renewable Energy System for Residential Applications Using Particle Swarm Optimization

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Abstract

We propose a hybrid off-grid energy system that comprises photovoltaic panels, wind turbines, diesel generators, and a battery bank. The proposed system could be adjusted to reflect real world conditions in order to optimize the cost of energy. Using Particle Swarm optimization searching methods, an optimal combination that follows load demand data of a typical house is found. From this configuration, the optimal mix that minimizes the levelized cost of energy (LCE) is formed and is found to be comparable to the cost of grid electricity.

Keywords: off-grid, hybrid, Particle Swarm optimization (PSO), Levelized Cost of Energy (LCE);

Nomenclature

This part includes explanation of the symbols used in Equations *1* and *2*, represent the core of the *PSO* algorithm [2,4,12,17,24,30].

V_i^K: denotes the velocity of particle ***i*** at the K_{th} iteration (scalar value).

V_i^{K+1}: the updating the velocity of particle i at the $(K+1)_{th}$ iteration (scalar value).

X_i^k: denotes the position of particle ***i*** at the K_{th} iteration (scalar value).

X_i^{k+1}: the updating the position of particle i at the $(K+1)_{th}$ iteration (scalar value).

w: weighting inertial coefficient; its value is typically between *0.8* and *1.2*, which can either dampen the particle's inertia or accelerate the particle in its original direction. Thus a large value of w makes the algorithm constantly explore new areas without much local search and hence fails to find the true optimum. To achieve a balance between global and local exploration to speed up convergence to the true optimum, an inertia weight w whose value decreases linearly with the iteration number has been used.

c_1 : A cognitive (individual) learning coefficient; usually close to *2* and affects the size of the step the particle takes toward its individual best candidate solution.

c_2: A social (group) learning coefficient; is typically close to *2* and represents the size of the step the particle takes toward the global best candidate solution the swarm has found up until that point.

The parameters c_1 and c_2 denote the relative importance of the memory (position) of the particle itself to the memory (position) of the swarm.

r_1 and r_2 are uniformly distributed random numbers in the range *0* and *1*.

The random values r_1 in the cognitive (individual) component and r_2 in the social (group) component cause these components to have a stochastic influence on the velocity update. This stochastic nature causes each particle to move in a semi-random manner heavily influenced in the directions of the individual best solution of the particle and global best solution of the swarm.

P_{best}^k: Every particle has a memory of its own best position; denoted by personal best. It is the best experience of the particle i .

g_{best}^k: In addition to this personal best there is a common best experience – among the members of the swarm denoted by global; global common experience among the members of the swarm.

Each particle tries to modify its position using the following information:

1. The current positions, X_i^k
2. The current velocities, V_i^K
3. The distance between the current position and personal best; $P_{best}^k - X_i^k$
4. The distance between the current position and the global best; $g_{best}^k - X_i^k$

The three terms of Equation 1:

$w^k.V_i^K$: This first term is the inertia component, responsible for keeping the particle moving in the same direction it was originally heading.

$c_1.r_1.(P_{best}^k - X_i^k)$: This second term, called the cognitive (individual) component, acts as the particle's memory, causing it to tend to return to the regions of the search space in which it has experienced high individual fitness.

$c_2.r_2.(g_{best}^k - X_i^k)$: This third term, called the social (group) component, causes the particle to move to the best region the swarm has found so far.

1. Introduction

Rural communities face a major obstacle in sourcing their modest energy needs; mainly lighting and electric appliances. So, it is difficult for rural households living off-grid to keep their lights on affordably and reliably levels; a major impediment to the development of their

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communities. This is even more evident in developing countries [1-5].

Also, sometimes it is cost prohibitive to connect them to the nearest electricity grid; a problem known as "*the last mile problem*" and "power loss problem" [6] may make connecting them unattractive to major electric distributors. So the only practical solution is to generate electricity locally or what is called "*distributed generation*".

Distributed generation from renewable energy sources (*RES*) has attracted the attention of many policy makers, universities and scientists looking for practical and realistic off-grid methods of electric generation and storage that can effectively replace conventional fossil fuels of oil, gas and coal. Renewable energy sources allow the use of natural resources, but their intermittency would prove inadequate mainly when the wind is not blowing, the sun is not shining, or the rivers are shallow. However, combining these natural renewable energy sources with conventional diesel generation and energy storage systems in "*hybrid renewable energy systems*" (*HRES*) may offer a reliable electric distributed generation and minimal diesel requirements to cope with the "worst month" problem [7]. *HRES* advantages include best use of the renewable power generation technologies operating characteristics and efficiencies higher than that could be obtained if a single power source is used [8]. The utilization of two or more *RES* may provide an economic solution as well for off-grid locations with significant weather changes and seasonal variations. It can be either grid connected or stand-alone mode. Stand-alone or off-grid is preferable due to recent advances in renewable energy technologies and highly efficient power electronics converters which are used to convert the unregulated power generated from renewable sources into useful power where it is required at the load end [9]; eliminating "the power loss problem" altogether.

Furthermore, *HRES* addresses *RES* limitations in terms of flexibility, efficiency, reliability, emissions and economics:

- Fossil fuel flexibility: Usually off-grid systems would rely solely on diesel generators, but due to the high cost of sourcing fossil fuel, diesel-based electric generation became uneconomic and costly.
- Reliability and cost are two of *HRES* advantages: it is possible to confirm that hybrid generation systems are usually more reliable and less costly than systems that rely on a single source of energy [5, 10-12].
- The rise of importance of renewable energy sources that fill the gap between nonrealistic free energy sources such as nuclear fusion and the need to provide electric services during the day from wind and solar panels when the sun shines and at night from the wind and battery storage.
- In various research papers [13-18, 2], it has been proven that hybrid renewable electrical systems in off-grid applications are economically viable; especially in remote locations. In addition, climate can make one type of hybrid system more profitable than another type. For example, photovoltaic hybrid systems (Photovoltaic–Diesel–Battery) are ideal in areas with warm climates [5,19].
- Lastly, it has been studied that due to the high initial cost of the system, government subsidies are required to adopt the system on a large-scale basis in remote areas [20,21]. Even though the cost of distributed generation of electricity from most of the hybrid energy systems are higher than that of the national grid electricity tariff, "the last mile problem" makes the cost of national grid extension to these remote areas difficult and uneconomical [5,16,17].

A common solution for off-grid power supply in small and medium-sized energy systems is a fuel generator set [22]; however, the following current developments have sought to improve the competitiveness and desirability of alternative off-grid hybrid renewable energy systems:

- Steeply decreasing production costs of renewable energy technologies like solar, wind and biomass caused a boom in the respective technologies in developed countries,
- Expanding research in electric storage devices sparked by the plans of several countries to use electric vehicles in the near future,
- Increasing environmental concerns and awareness of climate changes provoked by CO_2 emissions produced by the combustion of fossil fuels and
- Increasing operation costs for fuel generator sets due to rising oil prices.
- Several literatures have studied the sizing of hybrid energy systems:
- A simple general method for the optimization of the power generated from Hybrid Renewable Energy Systems (*HRES*) to achieve a typical house electric load as an example was presented in [6]. Particle Swarm Optimization Technique (*PSO*) is utilized as the optimization searching algorithm due to its advantages over other techniques for minimizing the "Levelized Cost of Energy" (*LCE*) with an acceptable production rate and minimal power loss [6].

Others [2,4,17,23,24] concluded that focusing on the installation cost alone is not enough for a hybrid renewable energy system (*HRES*) sizing methodology and the sizing model will be based on a simplified cost analysis. Besides the installation cost, Operation and maintenance (*O&M*) costs take up a large proportion of the overall cost of the system over its lifetime and must be taken into consideration. Thus, a method was developed to calculate long-term energy production costs for a hybrid wind–diesel system by taking into consideration fixed and variable costs of maintenance, operation and financing, and initial costs [2,4,17,23,24].

Alternatively**,** in [25] an algorithm was developed to optimize the size of a standalone hybrid wind–diesel system considering reactive power balancing conditions.

The optimal combination of components of a hybrid renewable energy system (HRES) were evaluated to meet the power demand and its reliability considering the loss of load probability (*LOLP*) [26].

The loss of load probability (*LOLP*) sensitivity analysis on total installation cost of the considered hybrid renewable energy system (*HRES*) was studied in [27].

From a different perspective, authors in [28] described an optimal energy storage sizing method by considering the compensation cost of wind power and load curtailment. Furthermore, authors in [1] researched the optimal size of batteries and diesel generator usage in a hybrid system which consists of wind turbines, photovoltaic panels (*PV*), diesel generator and battery storage. They introduced a sizing model that predicts the optimum configuration of a hybrid system and implemented it as a graphical user interface. In particular, their paper's sizing model simulates real time operation of the hybrid system, using the annual measured hourly wind speed and solar irradiation. The benefit of using time series approach is that it reflects a more realistic situation; here, the peaks and troughs of the renewable energy resource are a central part of the sizing model [1].

A general model of a hybrid off-grid energy system using linear programming methods was developed in [29]. This algorithm can be adjusted to reflect real conditions in order to achieve economical and ecological optimization of off-grid energy systems. The operation of this model was tested in two real off-grid energy systems, where both optimization processes resulted in hybrid energy systems, utilizing photovoltaic (*PV*), lead-acid batteries and a diesel generator as a load-balancing facility [29].

2. Particle swarm optimization, *PSO*

Particle Swarm Optimization simulates the social behavior of birds flocking or other natural creatures. Each bird represents a feasible solution in *PSO*. The solution in this case if two vectors representing position in solution space and a velocity. *PSO* in this case attempts to discover optimal solution through iteratively calculating the position solutions and modifying the velocities to follow the best known solutions. This is similar to birds following their leader in a spectacular view of intelligence. *PSO* was invented by Kennedy and Eberhart [30] and represents an important population-based metaheuristic algorithm. Using iterative methodology, the particles fly through the

N-dimensional space to discover the global optimal. Two main equations are traditionally used to govern the PSO namely velocity equation and position equation.

$$V_i^{K+1} = w^k.V_i^K + c_1.r_1.(P_{best}^k - X_i^k) + c_2.r_2.(g_{best}^k - X_i^k) \quad (1)$$

Equation 1 shows the velocity equation for the *PSO* algorithm in an iterative manner. The *k+1* iteration velocity for particle *i* is a combination of a memory value of the same velocity multiplies by a inertia parameter *w*, and a tendency value towards the current best value P_{best} and the global best g_{best} for the k^{th} iteration multiplied by a limiting acceleration constant values c_1 and c_2. Random variables r_1 and r_2 are used to enhance the search through varying the tendency components from iteration to iteration and from particle to another particle.

$$X_i^{k+1} = X_i^k + V_i^k \quad (2)$$

Equation 2 shows the position equation for the *PSO* algorithm. This is a simple linear distance calculation assuming the time difference equal to iteration difference between the *k+1* and k which is *1*. To assist the *PSO* in focusing in finding the optimal value, the velocity memory value inertia factor is reduced iteratively through the use of Equation 3.

$$w = w_{Max} - \left(\frac{w_{Max} - w_{Min}}{iter}\right) \times iter \quad (3)$$

where w_{Max} and w_{Min} are the initial and final values of the inertia weight, respectively, and $iter$ is the maximum number of iterations used in *PSO*. The values of w_{Max} = *0.9* and w_{Min} = *0.4* are commonly used.

A full schematic for the operation of the *PSO* is shown in Figure 1 below.

3. Hybrid system optimization Algorithm

The algorithm is shown in Figure 2. Initially, hourly solar irradiance (*kW/m*^{2}) and wind speed (m/s) for the University of Jordan with Latitude: 32° 00' 30.00" N and Longitude: 35° 52' 13.19" E were obtained using HOMER, [31]. Such data were used in order to determine the feasibility of our system and to perform the optimization. An energy load profile, or consumption profile; explains how energy used throughout the day, is obtained. The load profile is assumed constant all over the year, and it is also integrated to the data tables extracted from HOMER.

We then obtain the produced power *using rate 1 kW* using the following simplified equations:

$$P_w(kW) = \begin{cases} k_w \times v_w\,; & 3 < v_w < 25 \\ 0; & otherwise \end{cases} \quad (4)$$

where P_w is the wind generated power, v_w: is the wind speed, m/s, and $k_w = 0.03$ is a constant considered for simplified *LCE.*

$$P_s(kW) = k_s * SI \ (kW/m^2) \quad (5)$$

where P_s: the solar generated power, *SI* is the solar irradiance; the power per unit area received from the sun, and $k_s = 1.9$ is a constant considered for simplified *LCE.*

The *PSO* particle represents a solution (not optimal yet) for the system that is composed of three parameters and a complementary fourth:

1. Solar system solution *kW*,
2. Wind solution *kW*,
3. Battery storage solution *kWh* and
4. Generator maximum rated capacity in *kW.*

For each particle, the system is run for a full year and for each hour of the year. We calculate the extra needed power which is the power produced by both solar and wind that is more than the household load power needed as in Figure 3.

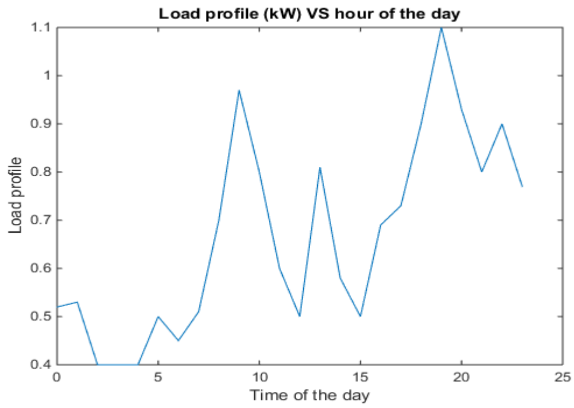

Figure 3. Load Profile

The algorithm then goes into deciding if this amount can be stored into the battery system and if so, the power is stored into the battery. Otherwise, the power is dumped. If the extra power turned to be negative that is less power is generated than load profile power needed.

If the power stored in the battery is greater than the needed power; it is pulled from the battery; otherwise we use the generator to generate the extra amount. Now we modify the capacity of the generator according to the new requirement.

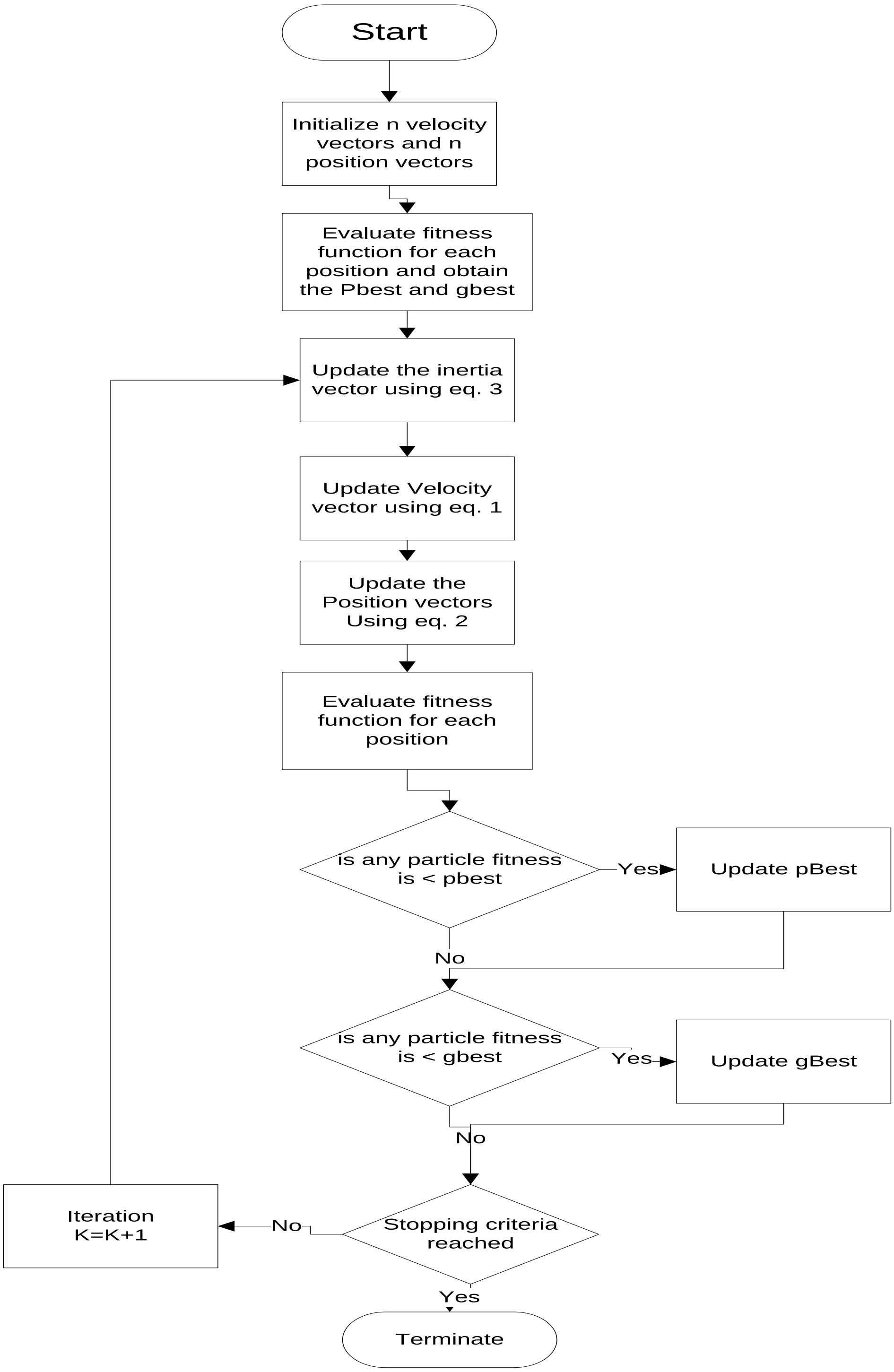

Figure 1. PSO flow chart

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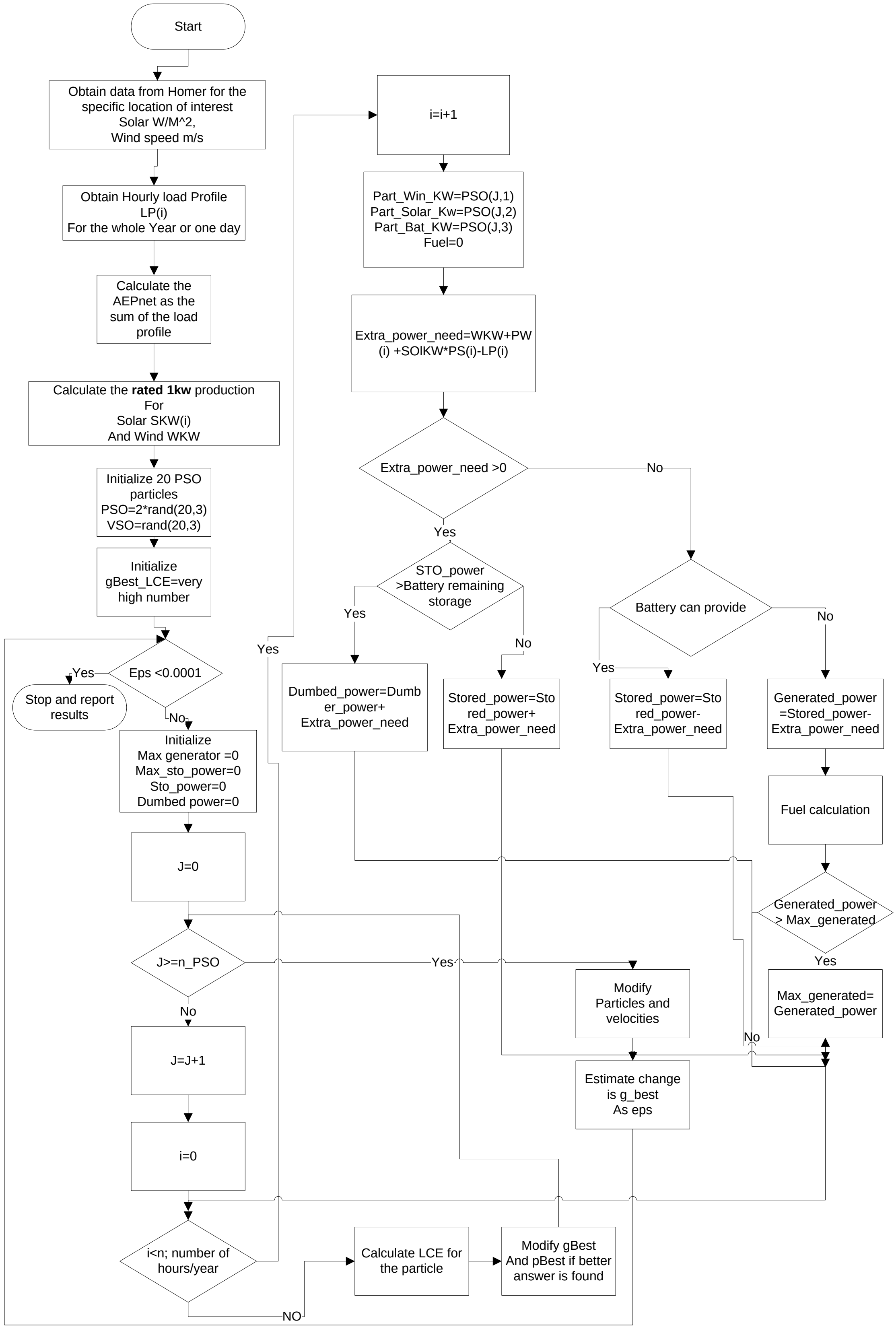

Figure 2. Hybrid system optimization Algorithm

The model of the fuel consumption as a function of the power generated is approximately:

$$F_c = 3.2\times10^{-6}P_F^3 + 1.0\times10^{-3}P_F^2 + 0.4PP_F + 2.2 \qquad (6)$$

where F_c is the fuel consumption in liter/hour and P_F is the power generated by the diesel generator in kW [1].

The total required power is used to calculate the levelized cost of energy (*LCE*), by dividing the total sum of the cost by the net Annual Energy Produced (*AEPnet*) as follows for each solution, [6]:

$$\mathrm{LCE} = \frac{(\mathrm{CRF}\times\mathrm{TPI})+(\mathrm{O\&M})+(\mathrm{LO\&R})}{\mathrm{AEP_{net}}} \qquad (7)$$

where: *TPI* is the total plant investment and in this work it is defined as $TPI = (P_s\times C_S + P_w\times C_W + P_F\times C_F + Bat\times C_B)$; where C_S is the cost of solar power \$/kW, C_W is the cost of wind power \$/kW, C_F is the cost of diesel generated power (Fuel) \$/kW, and C_B is the cost of Battery energy \$/kWh, *CRF* is the Capital Recovery Factor given as:

$$CRF = \frac{i(1+i)^n}{((1+i)^n-1)} \qquad (8)$$

where i is the interest rate (7.5%) and n is the operational life (25 years), and CFR=0.09. *O&M* is the annual Operating and Maintenance cost, and *LO&R* is the periodic Levelized Overhaul and Replacement cost.

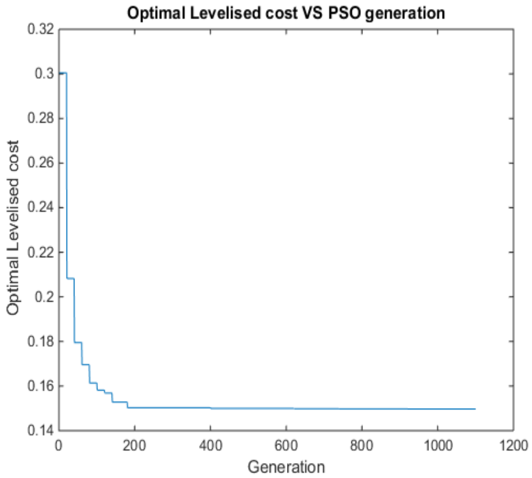

Figure 4. Optimal LCE

The g_{best} and the P_{best} is modified and the PSO particles and velocities are modified according to Equations 1 and 2. In case the modifications of the g_{best} is less than the *eps;* which is the convergence criteria; then we have an optimal solution and the algorithm is stopped as shown in Figure 4.

4. Results and Discussion

Due to the variability in prices of solar panels, wind turbines and battery units; we have run the PSO algorithm for several probable prices of these items. Consequently, different solutions are obtained for these different actual or hypothetical situations. Table 1 shows the optimal results.

Table 1. Different optimal solutions with different assumptions

Prices \$/kWh				Solution kWh				Optimal LCE
Solar	Wind	Battery	Generator	Solar	Wind	Battery	Generator	
550	550	500	100	6	0.8	0.3	0.77	0.148
550	550	100	100	3	1.78	0.63	0.32	0.087
550	550	45	100	2.75	1.76	0.70	0.34	0.071
300	***550***	***45***	***100***	***3.82***	***0.28***	***0.85***	***1***	***0.057***
300	550	100	100	5.54	0.47	0.44	0.95	0.07
300	300	100	100	5.02	1.26	0.41	0.65	0.068
300	300	45	100	3.65	0.90	0.75	0.81	0.056

From the table, we notice that the price of the batteries is the decisive factor in the optimal capacity of the HRES system. If we reduce battery prices from 500 to 45, we can reduce the capacity of the needed system from (6 kW solar, 0.8 kW wind) to (3.82 kW solar, 0.28 kW wind). Furthermore, reducing the prices of solar and wind will likely increase their contribution to the optimal solution.

In Table 2, we compare our LCOE results to similar research reported in [32-36].

Table 2. Comparison of Obtained Results with Previous Similar Research

Reference Year	LCOE \$/kWh	Notes
[32] 2018	0.37	The annual average wind speed is 2.22 m/s, which is considered inadequate for wind energy production. The monthly average irradiance value is minimum in August, with the value of 3.90 kWh/m2/day and maximum in March having a value of 6.05 kWh/m2/day.
[33] 2017	0.25	The annual average solar irradiation and wind speed are 5.57 kWh/m2/day and 7.29 m/s, respectively.
[34] 2019	0.22	The annual average global solar radiation (5.23-6.57 kWh/m2/day) as well as substantial wind-speed (3.0-4.37 m/s)
[35] 2019	0.12	The annual average wind speed of 3.6 m/s Similarly, average value of daily solar radiations was estimated to be 4.13 kWh/m2/day
[36] 2015	0.08	The annual average wind speed is 4.67 m/s scaled annual average radiations are 5.45704 kWh/m2/day
Our work	**0.057**	**(3.82 kW solar, 0.28 kW wind)**

Comparing LCOEs as shown in Table 2 need to be considered with caution as the LCOE calculation depends heavily on the following assumptions which must be provided and justified [37]:

- Degradation rate of solar panels efficiency over their lifetime.
- Scale, size and cost, including cost breakdown (residential, commercial, and utility scale).
- Capacity factor, solar insolation, geographic location, and shading losses.
- Lifetime of project and financial terms: financing (interest rate, term, equity/debt ratio cost of capital), and discount rate.
- Additional terms: inflation, incentives, credits, taxes, depreciation, carbon credits etc.

Since the inputs for the algorithm are highly variable; there is a need for using sensitivity analysis to represent actual variable distributions so that overconfidence in a single set of assumptions may be avoided.

5. Conclusions

During the course of this crucial study presented in this paper; we observed that the *PSO* searching technique tends to converge well after a short period of time with an optimal solution. Also, when using a lower battery price, the optimal solution tends to use lower capacity for wind and solar. Furthermore, because of the variability in both solar and wind, the best solution will have both; but the amount of each in the optimal solution will depend on its cost.

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