Chapter 3 PSO-Based Optimization of Levelized Cost of Energy for Hybrid Renewable Energy System



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Abstract The chapter aims to optimize the levelized cost of energy (LCOE) for a sample hybrid renewable energy system (HRES) consisting of power sources such as solar photovoltaic, wind and diesel generators. The variation of life cycle cost of the system reflected by the LCOE is computed for different generation capacity factors for a time period of 24 h. The interest rate is taken as 10%, the capacity recovery factor is assumed to be 0.1175 and the life span of the hybrid generating system is considered to be 20 years. The optimal LCOE computed using a traditional solver is compared with the particle swarm optimization technique.

Keywords Hybrid renewable energy system (HRES) · Levelized cost of energy (LCOE) · Interior-point algorithm · Particle swarm optimization (PSO)

Nomenclature

CRF	Capacity recovery factor
IC	Initial capital cost (€/kW)
AE	Annual operating expenses (€/kW)
AEP	Annual energy production (kW)
i	Interest rate (%)
n	Operational life (years)
AC	The annualized costs (insurance, other expenses) (€/kW/year)

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O&M	Operation and maintenance cost (€/kW/year)
CF	Net capacity factor
8760	Hours per year
$NS_1NS_2NS_N$	Number of solar power sources for different capacity
$NW_1NW_2NW_M$	Number of wind power sources for different capacity
$ND_1ND_2ND_P$	Number of DG power sources for different capacity
NS _{it}	Number of solar units generating at hour 't'
CS_i	Capacity factor of solar <i>i</i> th unit
NW_{it}	Number of wind power units generating at hour 't'
CW _i	Capacity factor of wind power <i>i</i> th unit
ND _{kt}	Number of DG units generating at hour 't'
CD_k	Capacity factor of DG <i>i</i> th unit
PD(t)	Demand at hour 't'
PL(t)	Losses at hour ' <i>t</i> '

1 Introduction

In order to meet the rising demand of electric power along with economic considerations governed by paying capacity of consumers and environmental issues, there is a need to switch to renewable energy sources for remote area electrification in place of traditional sources. Conventional sources are depleting while renewable energy sources are non-exhaustible and can be found in abundance in our planet at particular locations. Some of the promising renewable sources of power are solar, wind, tidal and geothermal [1, 2]. The location plays a very important role in the availability of renewable sources which differs as per location. In order to meet the demand in an optimized way, the hybrid system of renewable energy sources can be used. In India, the grid-tied installed PV capacity also saw a drastic increment of around 40% between the years 2017 and 2018 from 15.7 to 22.9 GW [3–5]. This major achievement in the solar power industry is mainly due to two factors, viz. innovative technologies that are able to reduce the manufacturing costs in the past years by near about 100 times and several government schemes that are focused on providing larger incentives for the power developers and consumers [6, 7].

The LCOE is used as a measure of comparison of different electricity generating methods on a regular basis. The LCOE can also be related to the term as the average minimum price at which electricity must be sold in order to break-even over the lifetime of the project [3, 8]. The LCOE, in other words, can also be defined as the cost that can be given or assigned to every energy producing unit by the system over a predefined period, then this will be equal to the total life cycle cost (TLCC) including depreciation, maintenance cost, etc., in addition to the operating cost which may be negligible for renewable energy sources. The optimum design sizing is very important for solar-wind power generation systems with battery banks [9, 10]. The optimal

sizing using an efficient optimization method can help to guarantee the lowest investment with a reasonable and full use of HRES, so that the system can work optimally with optimal configurations in terms of investment and reliability requirements for the given/forecast power demand. In this chapter, a model HRES system consisting of solar photovoltaic, wind and diesel generators have been selected for investigation. The energy output of renewable energy sources and load are dynamic in nature; hence, for meeting load demand, a conventional diesel generator is also included in this study. For the reduction of cost of energy to meet the pocket of consumers, optimization is done by reducing LCOE using traditional technique and PSO technique. Section 2 of the chapter describes the HRES and formulates LCOE; in Sect. 3, the optimization problem is formulated with equality/inequality constraints and limits; Sect. 4 discusses and summarizes the result and Sect. 5 concludes the chapter.

2 **Problem Formulation**

The combination of more than one renewable energy source even with the conventional source of energy called to be HRES [11, 12]. HRES is advantageous for reliability and cost to conventional source. Figure 1 shows the hybrid system of solar PV power source, wind power source and DG.

This is an assessment of the economic lifetime energy cost and lifetime energy production shown in Eqs. (1) and (2) and can be applied to essentially any energy technology [8, 13, 14].

Computational of LCOE for HRES could be written as follows:



Fig. 1 PV-wind-diesel-based hybrid renewal energy system

$$LCOE = \frac{\text{Life cycle cost}}{\text{Life time energy production}}$$
$$LCOE = \frac{(\text{CRF} * \text{IC}) + \text{AE}}{\text{AEP}_{\text{net}}}$$
(1)

LCOE =
$$\frac{\left(\left[\frac{i(1+i)^{n}}{(1+i)^{n}-1}\right] * \text{ICC} + (\text{AC} + [\text{O&M} * n])\right)}{8760 * \text{CF}_{\text{net}}}$$
(2)

3 Optimization of LCOE

The objective is to minimize LCOE of HRES which consisting of solar power units, wind power units and DG units [8, 15].

$$Min LCOE(NS, NW, ND.G)$$
(3)

Subject to

min
$$\sum_{t=1}^{T} \text{LCOE}(\text{NS}_1\text{NS}_2\dots\text{NS}_N, \text{NW}_1\text{NW}_2\dots\text{NW}_M, \text{ND}_1\text{ND}_2\dots\text{ND}_P)$$
 (4)

3.1 Power Generation Equality/Inequality Constraint

The power generated from each source must be less than or equal to the maximum capacity of the source as:

$$P_{\text{gen}} = \sum_{i=1}^{N} (\text{NS}_{it} * \text{CS}_i) + \sum_{j=1}^{M} (\text{NW}_{jt} * \text{CW}_j) + \sum_{k=1}^{P} (\text{ND}_{kt} * \text{CD}_k) - \text{PD}(t) - \text{PL}(t)$$
(5)

Inequality constraints

$$0 \le \mathrm{NS}_{it} \le \mathrm{NS}_N \quad \forall i = 1, 2 \dots N \tag{6}$$

$$0 \le NW_{jt} \le NS_M \quad \forall j = 1, 2 \dots M \tag{7}$$

$$0 \le \mathrm{ND}_{kt} \le \mathrm{NS}_P \quad \forall k = 1, 2 \dots P \tag{8}$$

4 Results and Discussion

4.1 Test Case Description

In this chapter, LCOE is computed for a HRES with 10 solar units each of 0.53 kW, 15 wind power units each of 1.5 kW and 5 DG units each of 2.5 kW. Losses are assumed to be 5% of demand. It is assumed that the renewable units of the HRES are operating with battery support to deliver the demand at all times. However, the battery modeling is not included in this chapter for the sake of simplicity. Computation is done on an hourly basis for 24 h' time horizon. The load profile is presented in Table 1, and the cost data for the HRES is given in Table 2. Capacity recovery factor, interest rate, life span as 0.1175, 10% and 20 years for HRES, respectively.

4.2 Optimization of LCOE

Results of optimal generation allocation for the HRES with interior-point algorithm using traditional solver '*fmincon*' on MATLAB platform for one day are shown in Table 3 for capacity factors of 0.3, 0.6 and 0.8 for solar, wind power and DG units, respectively.

The results clearly indicate that the optimization is successful in minimizing LCOE with the fulfillment of equality constraint given by (5).

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Load (kW)	20.30	17.50	16.80	14.00	16.80	18.90	24.50	27.30
Hours	1	2	3	4	5	6	7	8
Load (kW)	25.20	22.05	21.00	21.00	21.00	21.00	20.65	21.35
Hours	9	10	11	12	13	14	15	16
Load (kW)	27.30	31.50	34.30	34.30	31.50	32.20	28.00	21.70
Hours	17	18	19	20	21	22	23	24

 Table 1
 Load profile for time horizon of 24 h [16]

Table 2 Description of	Parameters	Cost/units					
HRES for computation of	Solar DV system						
	Solar F v system						
	Initial investment cost (€/kW)	2832.00					
	Annual investment cost (€/kW)	333.00					
	M&O cost (€/kW/year)	56.70					
	Number of units	10					
	Wind power						
	Initial investment cost (€/kW)	5832.00					
	Annual investment cost (€/kW)	685.02					
	M&O cost (€/kW/year)	116.64					
	Number of units	15					
	DG system	·					
	Initial investment cost (€/kW)	148.00					
	Annual investment cost (€/kW)	70.01					
	M&O cost (€/kW/year)	6.4					
	Number of units	5					

4.3 Effect of Capacity Factor on Optimal Value of LCOE

The effect of capacity factor on LCOE is analyzed by varying the capacity factor from 0.2 to 1 for solar units, wind power units and DG units. The results are plotted for the different combination cases in Figs. 2, 3, 4, 5 and 6. The LCOE is plotted for different combinations of CF values of DG and wind units while the CF of solar units is fixed at 0.2, 0.4, 0.6, 0.8 and 1.0, respectively, in Figs. 2, 3, 4, 5 and 6.

It is concluded from the results that the value of LCOE reduces as the capacity factors increase. For each case, the LCOE is least when the CF is 1.

4.4 Convergence Characteristics of the Solver

For each of the above 25 cases analyzed, 125 runs were conducted. For each case 134–135 iterations were required for convergence. Table 3 convergence behavior was obtained for each case. Figure 7 shows the convergence characteristic for $CF_s = 0.3$, $CF_w = 0.6$ and $CF_d = 0.8$. Similar curves were obtained for all other tested cases.

Hours	PV power	Wind power	DG power	Demand	PL	Violation
1	0.207	8.859	12.249	20.300	1.015	-0.00007
2	0.203	5.865	12.307	17.500	0.875	-0.00009
3	0.135	5.402	12.103	16.800	0.840	-0.00008
4	0.083	2.239	12.378	14.000	0.700	-0.00001
5	0.132	5.378	12.130	16.800	0.840	0.00019
6	0.081	7.507	12.257	18.900	0.945	0.00018
7	0.141	13.495	12.088	24.500	1.225	-0.00017
8	1.106	15.154	12.405	27.300	1.365	-0.00011
9	0.142	14.423	11.895	25.200	1.260	-0.00008
10	0.061	10.920	12.172	22.050	1.103	-0.00010
11	0.101	9.734	12.215	21.000	1.050	-0.00044
12	0.101	9.734	12.215	21.000	1.050	0.00000
13	0.100	9.734	12.217	21.000	1.050	0.00054
14	0.102	9.733	12.215	21.000	1.050	-0.00023
15	0.111	9.338	12.233	20.650	1.032	0.00004
16	0.072	10.131	12.215	21.350	1.067	-0.00010
17	1.106	15.212	12.347	27.300	1.365	-0.00009
18	2.148	18.701	12.226	31.500	1.575	0.00004
19	1.278	22.356	12.381	34.300	1.715	-0.00017
20	1.318	22.313	12.384	34.300	1.715	-0.00020
21	2.165	18.846	12.064	31.500	1.575	0.00016
22	1.693	20.012	12.105	32.200	1.610	-0.00009
23	1.597	16.042	11.760	28.000	1.400	0.00004
24	0.058	10.558	12.169	21.700	1.085	0.00010

Table 3 Optimal power schedule of HRES for a day

4.5 Validation of Results Using Particle Swarm Optimization

The results of the traditional solver are compared with PSO which is a populationbased evolutionary technique. For computing the results for capacity factor 0.3, 0.6 and 0.8, the inertia constant 0.9–0.4 acceleration coefficient assumes to be 0.2 each, population size 20 and maximum no. of iteration be 100. Figure 8 shows convergence characteristics for PSO of different population size.

The evolutionary technique like PSO employ random operators, therefore, every time the algorithm is run gives slightly different results, hence, the practice is to compute result after taking few numbers of trial. Here, 10 trials are conducted and statically analyze is performed for different population size keeping the other algorithm variable fixed.



Fig. 2 LCOE of HRES with variation of CF of wind and DG ($CF_s = 0.2$)



Fig. 3 LCOE of HRES with variation of CF of wind and DG ($CF_s = 0.4$)

The results are tabulated in Table 4 where it can be seen that most consistent results are obtained for population size 20 and trial 10. The consistency results for different population size are plotted in Fig. 9.

The results of traditional solver compare PSO algorithm in Table 5 and it is observed that the both results are quite close, but the traditional solver performs slightly better than PSO algorithm because PSO is random algorithm which performs better for problem with discontinuous and non-differential objective function.



Fig. 4 LCOE of HRES with variation of CF of wind and DG ($CF_s = 0.6$)



Fig. 5 LCOE of HRES with variation of CF of wind and DG ($CF_s = 0.8$)

5 Conclusion

The chapter makes an attempt to solve the optimal sizing and allocation of a hypothetical HRES with the aim to optimize the LCOE. The LCOE concept helps in establishing the economic viability of the system with renewable energy sources over a long run. This exercise also helps for deciding a feasible tariff for the HRES.



Fig. 6 LCOE of HRES with variation of CF of wind and DG ($CF_s = 1.0$)



Fig. 7 Convergence characteristics

The optimal LCOE is computed using a traditional solver and the results are compared and validated using an evolutionary algorithm. The effect of capacity factor of the various generating units on the life cost is analyzed. The effect of population size on the performance is studied for the along with the convergence property. The results of both algorithms are found to be quite close. The study is expected to be useful for the emerging HRES worldwide.



Fig. 8 Convergence characteristic for different population sizes

Tabl	e 4	Optimal	data	LCOE	for	listed	population	size and	trial = 10
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Pop size	Max value	Min value	Mean value	SD
10	0.6673	0.2244	0.4789	0.0137
20	0.5822	0.2244	0.3820	0.0115
30	0.6516	0.2370	0.4479	0.0142
40	0.6743	0.2278	0.4325	0.0120
50	0.6743	0.2621	0.4569	0.0100



Fig. 9 Consistency comparison of PSO for different population sizes (NP)

Table 5 Comparison of results of traditional solver	Technique	LCOE (€/kW)	
with PSO	PSO	0.2500	
	Traditional solver	0.2489	

References

- Tran TTD, Smith AD (2018) Incorporating performance-based global sensitivity and uncertainty analysis into LCOE calculations for emerging renewable energy technologies. J Appl Energy 216:157–171
- Sunderland K, Narayana M, Putrus G, Conlon M (2016) Levelised cost of energy analysis: acomparison of urban (micro) wind turbines and solar PV systems. In: 51st International universities power engineering conference (UPEC), pp 1–6
- 3. Baum S, von Kalben Č, Maas Å, Stadler I (2018) Analysis and modelling of the future electricity price development by taking the levelized cost of electricity and large battery storages into account. In: 7th International energy and sustainability conference (IESC), pp 1–8
- 4. Gupta RA, Kumar R, Bansal AK (2015) BBO-based small autonomous hybrid power system optimization incorporating wind speed and solar radiation forecasting. Renew Sustain Energy Rev: 41:1366–1375.
- Fathima AH, Palanisamy K (2015) Optimization in microgrids with hybrid energy systems—a review. Renew Sustain Energy Rev 45:431–446
- Yang H, Lu L, Zhou W (2007) A novel optimization sizing model for hybrid solar-wind power generation system. J Solar Energy 81(1):76–84
- Javed MS, Song A, Ma T (2019) Techno-economic assessment of a stand-alone hybrid solarwind-battery system for a remote island using genetic algorithm. J Energy 176:704–717
- Amer M, Namaane A, M'Sirdi NK (2013) Optimization of hybrid renewable energy systems (HRES) using PSO for cost reduction. Energy Procedia 42:318–327
- Bilal BO, Sambou V, Kébé CF, Ndiaye PA, Ndongo M (2012) Methodology to size an optimal stand-alone PV/wind/diesel/battery system minimizing the levelized cost of energy and the CO₂ emissions. Energy Procedia 14:1636–1647
- Meena NK, Kumar A, Singh AR, Swarnkar A, Gupta N, Niazi K, Kumar P, Bansal R (2019) Optimal planning of hybrid energy conversion systems for annual energy cost minimization in Indian residential buildings. Energy Procedia 158:2979–2985
- Ghorbani N, Kasaeian A, Toopshekan A, Bahrami L, Maghami A (2018) Optimizing a hybrid wind-PV-battery system using GA-PSO and MOPSO for reducing cost and increasing reliability. Energy 154:581–591
- Guangqian D, Bekhrad K, Azarikhah P, Maleki A (2018) A hybrid algorithm based optimization on modeling of grid independent biodiesel-based hybrid solar/wind systems. Renew Energy 122:551–560
- Kennedy J, Eberhart R (1996) Particle swarm optimization. In: Proceedings of IEEE International conference on neural networks 4:1942–1948
- Ma T, Javed MS (2019) Integrated sizing of hybrid PV-wind-battery system for remote island considering the saturation of each renewable energy resource. J Energy Convers Manage 182:178–90
- 15. Irena (2012) Working chapter, renewable energy technologies: cost analysis series. International Renew Energy Agency, Volume 1: power sector, solar photovoltaics, June 2012
- Borowy BS, Salameh ZM (1996) Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system. IEEE Trans Energy Convers 11(2):367–375
- 17. Huneke F, Henkel J, Benavides GJA, Erdmann G (2012) Optimisation of hybrid off-grid energy systems by linear programming. Energy, Sustain Soc 2(1)