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Research Paper

Economical Based Optimal Sizing of Distributed Energy Resources Including Wind Turbines, Solar Cells and Fuel Cells Using Non-Dominated Sorting Method For Power Loss Reduction

Engineering

KEYWORDS : power loss, non dominated sorting approach, renewable energy

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ABSTRACT

this paper presents the multi objective optimization of distributed energy resources (DERs) in distribution system. The two objective functions that have been considered in this research are minimizing power loss of system and minimizing total cost of (DERs). The life cycle cost (LCC) concept is considered for cost analysis in this paper. Since the two objective functions which considered in this research are two conflicting objective, therefore a non dominated approach based NSGAII is employed to optimized the results. This technique addressed a set of results that based on the decision of operator one of solution can be selected.

1. INTRODUCTION:

The continuous increase in energy consumption, the rising cost and polluting nature of fossil fuels, and the increasing worry over global warming cause much attention to be focused on renewable energy sources. Wind and solar energy power generation are two of the most favored renewable power generation technologies [1] and they can be combined together to create a hybrid energy system. In general, multi-source hybrid energy systems have a higher quality and greater reliability than a system comprising a single resource [2]. Hybrid energy system is used in order to improve the overall system performance, and overcome the stochastic availability of wind and solar energy power generation [3, 4] . In this way, the shortcomings associated with wind and solar energy sources are removed through the support of the other sources in a natural or controlled way. Therefore, in spite of the unpredictable availability of solar and wind energy sources, hybrid systems usually present an acceptable performance [5].

In this paper, NSGAII algorithm has been proposed to determine the hybrid combination of DGs capacity and switch numbers in order to minimize; the total system real power loss, the cost of electrical energy produced by hybrid system and purchased from the main substation(s).

2. COST ANLYSIS

The economical approach, according to the concept of life cycle cost (LCC), is developed to be the best indicator of economic profitability of system cost analysis in this study. According to the studied system, the life cycle cost (LCC) takes into account the initial capital cost (***IC**$_{cap}$*), the present value of replacement cost (***Crep***) and the present value of maintenance cost (***Cmain***). Thus, LCC may be expressed as follows:

$$f_1(X) = LCC(DA) = IC_{cap} + C_{rep} + C_{main} \qquad 1$$

The initial capital cost for the hybrid system, (ICcap) is given by:

$$IC_{cap}(DA) = C_{PV} * C_{Unit,PV} + C_{FC} * C_{Unit,FC} + C_{WT} * C_{Unit,WT} \qquad 2$$

Where CPV, CUnit,PV are the total capacity (W) and unit cost (DA/W)of PV array respectively; CWT, CUnit, WT are the total capacity (W) and unit cost (DA/W) of the wind turbines set respectively; CFC, CUnit, FC are the total capacity (W) and unit cost (DA/W) of the fuel cells respectively.

The present value of replacement cost considering the inflation rate of component replacements (***f0***) and real interest rate (***kd***), the present value of replacement cost (***Crep***) can be determined as follows [6]:

$$C_{rep} = C_{Unit} C_{nom} \sum_{i=1}^{N_{rep}} \left[\frac{(1+f_0)}{(1+k_d)} \right]^{N_i / N_{rep} + 1} \qquad 3$$

Where ***Cnom*** is the nominal capacity of the replacement system component; ***CUnit*** is the unit component cost and ***Nrep*** is the number of component replacements over the system life period.

Also the present value of operation and maintenance cost of the hybrid system ***CO&M*** is expressed as [7]:

$$C_{O\&M} = \begin{cases} C_{(O\&M)_0} \left(\dfrac{1+f_1}{k_d - f_1} \right) \left[1 - \dfrac{1+f_1}{1+k_d} \right]^{L_p} & for \ k_d \neq f_1 \\ C_{(O\&M)_0} * L_p & for \ k_d = f_1 \end{cases} \qquad 4$$

Where ***f1*** is the inflation rate for operations; ***kd*** is the annual real interest rate and ***Lp*** is the system life period in years.

C(O&M)0 is the operation and maintenance cost in the first year. It can be given as a fraction “k” of the initial capital cost (***CIC***) is expressed as:

$$C_{(O\&M)_0} = k * C_{IC} \qquad 5$$

3. POWER LOSS OF SYSTEM

Minimizing the real power loss is selected as the second objective function for the optimal sizing of REGs. Reducing the real power loss of the distribution feeders is an important purpose of implementing REGs. The minimization of total real power losses of feeders over one life time period can be calculated as follows:

$$f_2(X) = \sum_{i=1}^{N_{br}} (R_i \times |I_i|^2) \qquad 6$$

where R_i and Ii are the resistance and the actual current of the ith branch, respectively. ^{N}br is the number of the branches.

4. NSGAII ALGORITHM

The computational algorithm of NSGA-II is used to address the hybrid renewable energy resources problem through the

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following steps:

Step 1 Initialization. In this step a population is generated randomly in the search space as initial solutions of the algorithm.

Step 2 objective evaluations. For each individual of the population, the values of objective functions are evaluated in this section.

Step 3 Non-dominated sorting. The NSGA-II algorithm sorts a population into distinctive non-dominated levels (fronts). Initially, it achieves the Pareto optimal set of the present population (RANK = 1), then it disregards temporarily these solutions and search again the Pareto optimal set among the residual individuals of the population (RANK = 2). This procedure is repeated until all fronts are recognized and allocated to all individuals. This attribute is one of the two features that illustrate the fitness of the solutions. The second feature is crowding distance.
Step 4 Crowding distance. After completing the non-dominated sorting, the crowding distance is applied to sort the individuals in the same front.

In order to estimate the density of solutions neighboring the i^{th} individual in each non-dominated set, the average normalized distances of the two adjacent neighbors for each objective function are calculated and summed all together, as follows [8]:

$$CD(X_i) = \sum_{j=1}^{m} \left| \frac{f_j(X_{i+1}) - f_j(X_{i-1})}{f_j^{max} - f_j^{min}} \right| \quad 9$$

Where $CD(X_i)$ is the overall crowding distance of solution X_i, m is the number of objective functions, $f_j(X_{i+1}), f_j(X_{i-1})$ are j^{th} objective function values of the two nearest neighbors of the i^{th} individual, f_j^{max}, f_j^{min} are the maximum and minimum values of j^{th} objective function.

Step 5 Selection. The binary tournament based selection carried out between two randomly chosen individuals from the population.

Step 6 Cross-over.

Step 7 Mutation
The above procedure except Step 1 is repeated for the maximum number of iterations. Fig.1 shows the NSGAII algorithm's flowchart.

In order to decision making, a fuzzy based method is applied in this paper to select the favored solution among non-dominated solutions. Through fuzzy set theory, a linear membership function assigned for each objective function Eq. (10) and (11) are used respectively, for normalizing monotonically decreasing and increasing objective functions [9].

$$\mu_i^k = \frac{f_i^{max} - f_i^k}{f_i^{max} - f_i^{min}} \quad 10$$

$$\mu_i^k = \frac{f_i^k - f_i^{min}}{f_i^{max} - f_i^{min}} \quad 11$$

f_i^{max}, f_i^{min} are the maximum and minimum values of i^{th} objective function.

Mathematically, none of the solutions in the trade-off region has a priority with respect to other solutions. Due to the subjective imprecise nature of the decision maker's judgment, a fuzzy satisfying method is applied here to select the preferred solution among non-dominated solutions. Through fuzzy set theory, each objective function is presented with a linear membership function.

If the objective function is monotonically decreasing, Eq. (10) is used for normalizing vice versa if the objective function is monotonically increasing Eq. (11) is applied.

The normalized membership function of the kth non-dominated solution is defined as follows:

$$\mu^k = \frac{\sum_{i=1}^{m} \mu_i^k}{\sum_{k=1}^{N_p} \sum_{i=1}^{m} \mu_i^k} \quad 12$$

Where Np is number of non-dominated solutions and m is number of objective functions.

The solution with the maximum membership value is selected as the best compromising solution.

Of course in order to decision making, a fuzzy based method is applied in this paper to select the favored solution among non-dominated solutions. Through fuzzy set theory, a linear membership function assigned for each objective function.

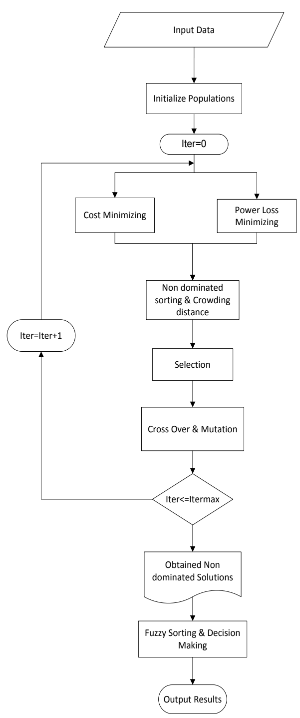

Fig.1.The proposed algorithm's flowchart

5. SIMULATION AND RESULTS:
In this section the results of hybrid clean energy resources optimization using proposed algorithm based environmental impact and economic analysis is presented. The hybrid system which simulated in this research is grid connected and it is supposed that the hybrid clean energy resources including photovoltaic cells, wind turbines and fuel cell is responsible to support a local.

Te information of the each system component, e.g. investment cost, operation and maintenance cost, fuel cost of fuel cell and utility grid are given in Table 1. Te one line diagram of 30-bus test system is shown in Figure 2. The system demand is 283.4 MW in all simulations.

Table.1. Specification of different energy sources and grid utility

	Rated capacity	Investment cost ($/kW)	Fuel cost ($/kWh)	O&M Cost ($/kWh)	Capacity Factor	Life time (year)
WT	400(kW)	4500	0	0.005	0.2	20
FC	400(kW)	3674	0.029	0.010	0.4	10
PV	400(kW)	6675	0	0.005	0.25	20

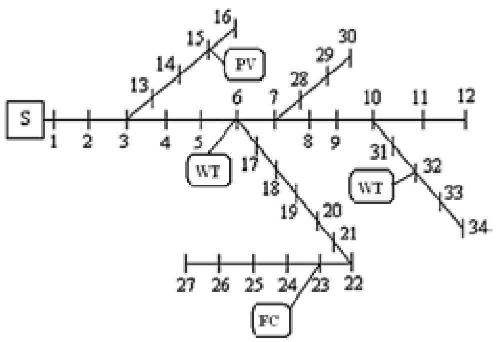

Fig.2.The 30 bus distribution test system at the presence of hybrid PV/WT/FC system

In this paper we have changed MATPOWER by adding NSGAII codes in order to implement the multi-objective OPF problem in power systems. Te parameters required for implementation of the NSGAII algorithm are listed in Table 2.

Table 2.Parameters of the NSGA-II algorithm

Max_Iter	Population Size	Crossover Rate	Mutation Rate
250	50	0.8	0.4

In this study a multi-objective optimal power flow problem is solved, the Pareto-optimal method is used in this case to solve compromise between the two objectives. Te user based on the importance of each goal and can find different solutions. After NSGAII apply the Pareto set, the best compromise solution is selected according to Equation (12). In this regard Equation (12) is computed for all non-dominate solutions, after sorting them according to their μ^k value, the best solution among them considers as the best compromised solution. Te best solution among the best compromise solution is studied. Figure 3 shows the curve of the solution is compromise.

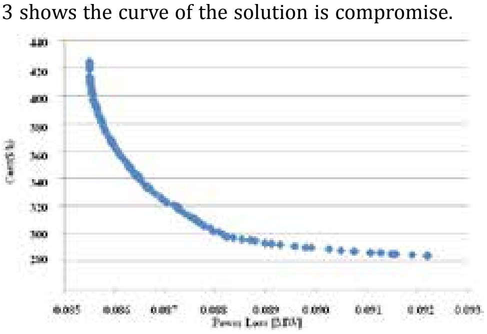

Fig.3.Some of the best non-dominated results

Table 3 shows some of the obtained non-dominated solutions between 15 non-dominated solutions. The obtained non-dominated solutions allow the system operators to use their personal preference in selecting any one of them for implementation. Table 4 shows the related variables for the obtained solutions. The optimum values of the non-dominated solutions for each objective function have been highlighted in Table 3. However with considering two conflicting objective function the best compromising solution is the solution with the maximum membership value. The best compromising solution with fuzzy ranking 1 is highlighted in the first row of Table 3. The corresponding normalized membership function is 0.0124843 and related power loss is 0.0851 and life cycle cost ($) is 312.045 ($/h).

Table 3.Some of the non-dominated solutions

Fuzzy Ranking	Power Loss (MW)	LCC ($/h)	Normalized membership function
1	0.0851	312.045	0.0124843
2	0.0855	315.023	0.0124253
3	0.0860	315.023	0.0124025
4	0.0866	320.342	0.0123903
5	0.0869	330.392	0.0123746
6	0.0870	330.634	0.0123532
7	0.0881	340.823	0.0123354
8	0.0887	340.922	0.0123212
9	0.0880	350.233	0.0123187
10	0.0891	350.322	0.0122959
11	0.0910	326.975	0.0122830
12	0.0921	360.621	0.0122423
13	0.0930	360.822	0.0122262
14	0.0934	365.193	0.0122128
15	0.0938	368.023	0.0122094

Table 4.Related decision variables for obtained non-dominated solutions

Fuzzy Ranking	P_PV,15 [kW]	P_WT,6 [kW]	P_WT,32 [kW]	P_FC,23 [kW]
1	167.40	98.431	185.43	12.46
2	180.41	119.60	198.25	13.60
3	197.85	13.630	190.34	10.00
4	190.03	130.02	200.42	20.00
5	190.87	140.42	210.32	20.33
6	195.44	110.82	210.12	10.00
7	193.38	115.82	200.45	15.23
8	210.82	10.000	195.12	15.54
9	200.35	110.62	193.67	7.861
10	200.86	115.52	190.87	20.73
11	201.28	18.261	180.54	30.43
12	195.89	15.191	180.34	40.43
13	193.25	110.39	210.65	100.0
14	180.90	120.52	195.76	10.32
15	179.26	115.24	205.32	15.64

As seen in Table 4 for the best compromising solution with fuzzy ranking 1 which is highlighted in the first row of Table 3. The corresponding normalized membership function is 0.0124843 and related power loss is 0.0851 and life cycle cost ($) is 312.045 ($/h) and related P_PV, 15 167.4 [kW], P_WT, 6 =98.431 [kW], P_WT, 32 =185.43 [kW], P_FC, 23 =12.46 [kW].

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6. CONCLUSION

This paper deals with optimal sizing of some preinstalled renewable energy resources with conventional distributed generation, e.g. fuel cell to support demand side in distributing system.

A non dominated sort algorithm based NSGAII is implemented to optimized the solutions. In the test system

Two wind turbines, one fuel cell and one photovoltaic arrays have implemented to optimal the system operation under two conflicting objective function. The first power loss reduction and second the minimization total cost. At the end, the user based on the importance of each goal and can find different solutions. After NSGAII apply the Pareto set, the best compromise solution is selected according to the fuzzy based decision ranking.

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