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# Minimizing Total Emission and Minimizing Total Cost of a Dispersed Renewable Energy Resources Using Non-dominated Sorting Algorithm and Comparison with Other Intelligent Methods

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ABSTRACT

This research deals with the environmental protection by avoiding of pollution of the usual combustion in conventional fossil plants which products SOx, particulates, CO, CO2 and various unburned or partially burned hydrocarbons. The idea of this research is investigation the utilization of dispersed distributed generations. In other words in this paper two wind turbines, one solar cell and one fuel cell at different buses of system are installed and only optimal sizing of these sources are purpose. Two types of distributed generations are considered in this paper. The first type is renewable energy resources e.g. solar cells and wind turbines and second type is conventional DGs e.g. fuel cell. Two objective function including total emission minimization and coat minimization as two conflicting objective function are considered in this research that are optimized using a non dominated based algorithm.



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## INTRODUCTION

The deregulated energy environment, among other effects, has favored the usage of DG sources connected near the energy consumers [1]. These sources comprise many technologies, such as diesel engines, wind turbine and fuel cells either in combined heat and power (CHP) operation or purely for electricity production, photovoltaic (PV), microturbines (MTs), hydroturbines, etc [2]. In [3] the optimum sizing of PV with energy storage systems for autonomous small islands has been studied. Of course various combinations of these technologies have been studied as a MG in stand-alone or gird-connected modes. In [4], the problem of the management of MG is solved without considering the balancing with the upper grid. In [5], the optimal sizing of a stand-alone hybrid power system, including wind/fuel cell via PSO, has been analyzed. Unit sizing and cost analysis of stand-alone hybrid wind/PV/fuel cell power generation systems has been presented in [6].In [7], techno-economic analysis of a stand-alone hybrid photovoltaic-diesel battery-fuel cell power system based on Net Present Cost (NPC) method has been proposed. In [8], the optimal sizing of hybrid wind/PV/diesel power generation unit in stand-alone mode has been analyzed. [9] has investigated the size optimization of a PV/wind hybrid energy conversion system with battery storage using simulated annealing. In [10], economic analysis of stand-alone and grid-connected hybrid energy systems has been studied.

***1.*** *Yearly total emission analysis:*

Some of the distributed generation units (DGs) which considered in the hybrid renewable system are inserting pollutant gases into atmosphere. The main polluting gases are CO2, NOx, SO2, CO and PM10.

The yearly total emission level produced by a hybrid set of DGs and utility grid can be expressed as follows[11]:

$$TEL = \sum_{i=1}^{N_{dg}} \sum_{j \in Tech} P_{DG,i} \times ER_j \times CF_j \times 8760 + P_{Sub} \times LF \times ER_{Grid} \times 8760 \tag{1}$$

where:

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$ER_j$ and $ER_{Grid}$ is emission rate of j[th] DG technology (kg/kWh) and Grid respectively and $N_{dg}$ is number of DGs.

***2.*** *Economic criteria based on lcc concept:*

It is pertinent that economic analysis should be made while attempting to optimize the size of hybrid system favoring an affordable unit price of power produced. 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. The LCC is defined as the total cost of the whole hybrid system. Four main parts are considered: PV array, Wind Turbine, the Fuel Cells and tank, and the converter. 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 ($C_{rep}$) and the present value of maintenance cost ($C_{main}$). Thus, LCC may be expressed as follows [12]:

$$LCC(DA) = IC_{cap} + C_{rep} + C_{main} \tag{2}$$

*2.1 The initial capital cost:*

The initial capital cost of each system component consists of the component price, the cost of civil work, installation and the connections. In this study, the civil work and installation costs are taken as 40% of PV generator price for PV part and 20% of the equipments including wind turbines, fuel cells and hydrogen tanks and converters. Then the initial capital cost for the hybrid system, ($IC_{cap}$) is given by:

$$IC_{cap}(DA) = C_{PV} * C_{Unit,PV} + C_{FC} * C_{Unit,FC} + C_{WT} * C_{Unit,WT} + C_{conv} * C_{Unit,conv} + C_{Tank} * C_{Unit,Tank} \tag{3}$$

Where $C_{PV}$, $C_{Unit,PV}$ are the total capacity (W) and unit cost (DA/W)of PV array respectively; $C_{tank}$, $C_{Unit,tank}$ are the total capacity (W) and unit cost (DA/W) of the tank respectively; $C_{WT}$, $C_{Unit,WT}$ are the total capacity (W) and unit cost (DA/W) of the wind turbines set respectively; $C_{FC}$, $C_{Unit,FC}$ are the total capacity (W) and unit cost (DA/W) of the fuel cells respectively and $C_{conv}$, $C_{Unit,conv}$ are the nominal capacity (W) and unit cost (DA/W) of the electrical converters respectively; and $C_0$ is the total constant cost including the cost of civil work and installation.

*2.2 The present value of replacement cost:*

The present value of replacement cost of a system component is the present value of all the replacement costs occurring throughout the system life time. As the life period of the hydrogen tank and converter are shorter than other equipments; the replacement cost of the hydrogen tank and converters have to be included in the cost analysis of the hybrid system. Considering the inflation rate of component replacements ($f_0$) and real interest rate ($k_d$), the present value of replacement cost ($C_{rep}$) can be determined as follows [13]:

$$C_{rep} = C_{Unit} C_{nom} \sum_{i=1}^{N_{rep}} \left[ \frac{(1+f_0)}{(1+k_d)} \right]^{N_i / N_{rep} + 1} \tag{4}$$

Where $C_{nom}$ is the nominal capacity of the replacement system component; $C_{Unit}$ is the unit component cost and $N_{rep}$ is the number of component replacements over the system life period.

*2.3 The present value of operation and maintenance cost:*

In its general form, the present value of operation and maintenance cost of the hybrid system $C_{O\&M}$ is expressed as:

$$C_{O\&M} = \begin{cases} C_{(O\&M)_0} \left( \frac{1+f_1}{k_d - f_1} \right) \left[ 1 - \frac{1+f_1}{1+k_d} \right]^{L_p} & for\ k_d \neq f_1 \\ C_{(O\&M)_0} * L_p & for\ k_d = f_1 \end{cases} \tag{5}$$

Where $f_1$ is the inflation rate for operations; $k_d$ is the annual real interest rate and $L_p$ 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 ($C_{IC}$ ) is expressed as:

$$C_{(O\&M)_0} = k * C_{IC} \tag{6}$$

***3.*** *Optimization:*

Multi-objective optimization problems with conflicting objectives may not hold just one solution, and in the most cases there is a number of solutions without an absolute preference amongst them. Hence, a multi-objective optimization problem with conflicting objectives aims to find the best compromise tradeoffs among the feasible solutions in the search space. These kinds of solutions are known as non-dominated solutions or Pareto solutions.

The set of non-dominated solutions or Pareto solutions, construct the Pareto front or front of non-dominated solutions. This set provides a number of options for decision makers to choose the best option with regard to the other quantitative or qualitative parameters. In general, a multi-objective optimization problem can be formulized as follows:

$$\min_{x\in X^{n_x}} f(x)=\{f_1(x) \quad f_2(x) \quad ,..., \quad f_M(x)\} \tag{7}$$

$$g(x)\le 0,\ h(x)=0 \tag{8}$$

Where $g(x)\le 0,\ h(x)=0$ , are the sets of the problem constraints that determine the boundaries of the feasible solution space in $n_X$ dimensional search space, and *f(x)* is an M dimensional vector of objective values. A map between decision variables of $x\in X^{Nx}$ and objective space of $f\in F^M$ is determined by objective functions.

## 4. *Nsgaii Algorithm:*

The computational algorithm of NSGA-II is used to address the hybrid renewable energy resources problem through the 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 [14]:

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

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.2 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 [15].

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

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

$f_i^{max}, f_i^{min}$ 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 $k^{th}$ 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.

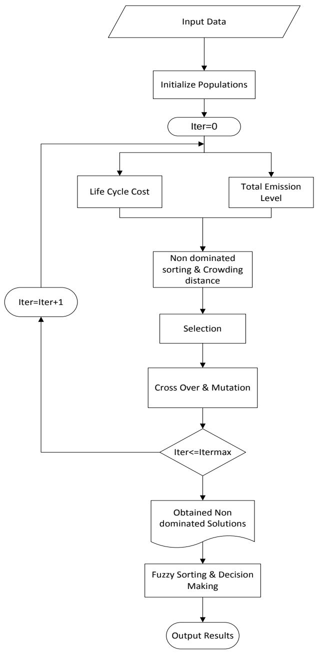


**Fig. 2:**The proposed algorithm's flowchart.

## **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 and emission coefficients 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.

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.

To demonstrate the effectiveness of the proposed approach, three cases with different complexity have been considered as follows:

**Case 1**: Minimize total operating cost.

**Case 2**: Minimize total emission.
**Case 3**: Minimize operating cost and emission at the same time.

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

| Energy source | Rated capacity (kW) | Investment cost ($/kW) | Fuel cost ($/kWh) | O&M cost ($/kWh) | Capacity Factor | Emission rate (kg/MWh) | | | Life time(year) |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | CO2 | NOX | SO2 | |
| WT | 400 | 4500 | 0 | 0.005 | 0.2 | 0 | 0 | 0 | 20 |
| FC | 400 | 3674 | 0.029 | 0.010 | 0.4 | 502.58 | 0.52163 | 3628.7 | 10 |
| PV | 400 | 6675 | 0 | 0.005 | 0.25 | 0 | 0 | 0 | 20 |
| Grid | -- | -- | -- | -- | -- | 921.25 | 2.2952 | 3.5834 | -- |

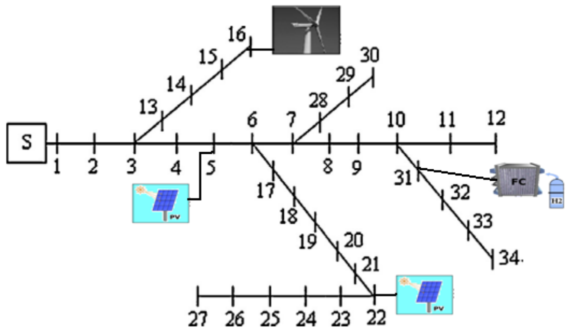


**Fig. 2:** The 30 bus distribution test system at the presence of hybrid PV/WT/FC system.

**Table 2:** Parameters of the NSGA-II algorithm.

| Max_Iter | Population Size | Crossover Rate | Mutation Rate |
|---|---|---|---|
| 250 | 50 | 0.8 | 0.4 |

Initially, each of the objective functions individual are examined then used Te Pareto-optimal method to obtain the optimal point by optimizing the two objectives simultaneously. Te results are shown in Tables 3, 4, 5 and 6.

In first case which minimizing total operating cost is objective function, the capability and power of proposed algorithm, it has been compared with new heuristic methods that results of this comparison are shown in Table 3. Algorithm has converged in 287.64 ($/h) which is the lowest cost. Convergence curve for this case is shown in Figure 3.

**Table 3:** Comparison of proposed algorithm with PSO, GA algorithms (Cost).

| Method | $P_{\_WT,5}$ [kW] | $P_{\_FC,5}$ [kW] | $P_{\_PV,5}$ [kW] | $P_{\_WT,12}$ [kW] | $P_{\_FC,12}$ [kW] | $P_{\_PV,12}$ [kW] | Cost($/h) | Emission(Ton/h) |
|---|---|---|---|---|---|---|---|---|
| NSGAII | 150.3 | 6.43 | 196.8 | 150.6 | 30.5 | 200.6 | 287.64 | 0.025622 |
| GA | 184.7 | 7.32 | 200.6 | 200.1 | 9.38 | 129.9 | 288.12 | 0.025812 |
| PSO | 199.5 | 5.28 | 200.3 | 177.8 | 2.82 | 165.8 | 286.86 | 0.026282 |

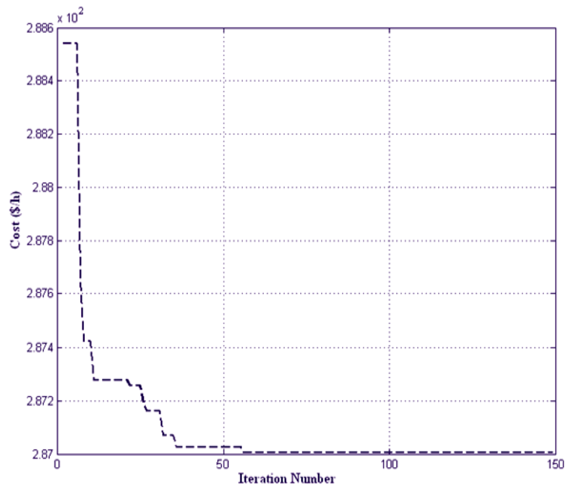


**Fig. 3:** Convergence plot for NSGAII for cost function.

In second case which minimizing total emission is objective function, the total amount of emission will be achieved by the proposed algorithm and the results are shown in Table 4. In this table the results obtained from the proposed algorithm is compared with GA and PSO algorithm. Results of Table 5 indicate how a reduction in NOx, SOx emission could be achieved by a change in generation dispatch schedules. In this case, the amount of pollution that can be emitted by the proposed algorithm is lower than other algorithms and it shows the ability of the proposed algorithm. Figure 4 shows the curve of convergence obtained in this case.

**Table 4:** Comparison of proposed algorithm with PSO, GA algorithms (Emission).

| Method | $P_{\_WT,5}$ [kW] | $P_{\_FC,5}$ [kW] | $P_{\_PV,5}$ [kW] | $P_{\_WT,12}$ [kW] | $P_{\_FC,12}$ [kW] | $P_{\_PV,12}$ [kW] | Cost($/h) | Emission(Ton/h) |
|---|---|---|---|---|---|---|---|---|
| NSGAII | 200.2 | 0 | 141.5 | 200.4 | 0 | 200.0 | 343.43 | 0.018532 |
| GA | 195.8 | 0 | 175.2 | 188.8 | 0 | 174.5 | 346.29 | 0.018412 |
| PSO | 174.3 | 0 | 139.6 | 198.2 | 0 | 173.3 | 344.65 | 0.018512 |

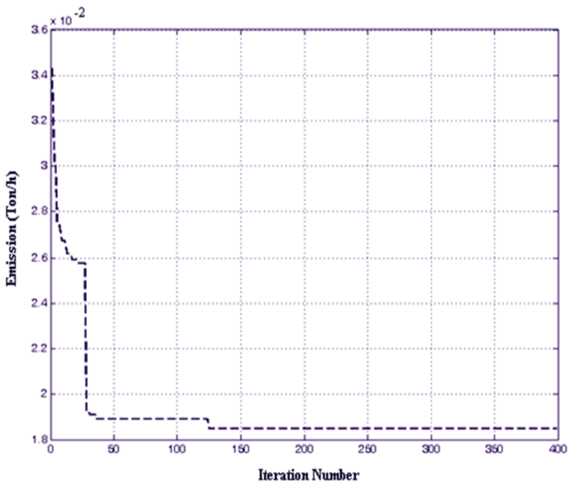


**Fig. 4:** Convergence plot for NSGAII for emission function.

In third case which 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 $\mu^k$ value, the best solution among them considers as the best compromised solution. Te best solution among the best compromise solution is studied. Figure 5 shows the curve of the solution is compromise.

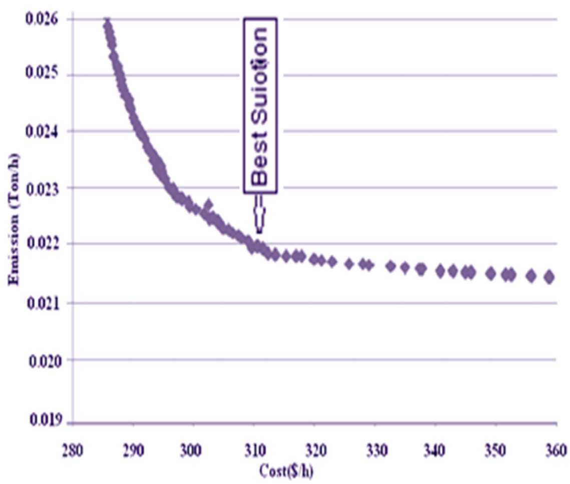


**Fig. 5:** Some of the best non-dominated results.

Table 5 shows some of the obtained non-dominated solutions between 25 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 6 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 5. 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 5. The corresponding normalized membership function is 0.0124843 and related emission is 0.022017 and life cycle cost ($) is 310.0236 ($/h).

**Table 5:** Some of the non-dominated solutions.

| Fuzzy Ranking | Emission (Ton/h) | LCC ($/h) | Normalized membership function |
|---|---|---|---|
| 1 | 0.022017 | 310.0236 | 0.0124843 |
| 2 | 0.022173 | 315.023 | 0.0124253 |
| 3 | 0.022273 | 315.023 | 0.0124025 |
| 4 | 0.022673 | 320.342 | 0.0123903 |
| 5 | 0.023112 | 320.392 | 0.0123746 |
| 6 | 0.023204 | 320.634 | 0.0123532 |
| 7 | 0.023353 | 320.823 | 0.0123354 |
| 8 | 0.023632 | 320.922 | 0.0123212 |
| 9 | 0.024071 | 324.233 | 0.0123187 |
| 10 | 0.024102 | 325.322 | 0.0122959 |
| 11 | 0.024385 | 326.975 | 0.0122830 |
| 12 | 0.024586 | 330.621 | 0.0122423 |
| 13 | 0.024782 | 330.822 | 0.0122262 |
| 14 | 0.025801 | 335.193 | 0.0122128 |
| 15 | 0.025874 | 338.023 | 0.0122094 |
| 16 | 0.025253 | 340.332 | 0.0121938 |
| 17 | 0.025732 | 340.493 | 0.0121876 |
| 18 | 0.026073 | 340.634 | 0.0121524 |
| 19 | 0.026182 | 350.742 | 0.0121398 |
| 20 | 0.026286 | 350.831 | 0.0121295 |
| 21 | 0.025564 | 350.923 | 0.0121134 |
| 22 | 0.025734 | 355.023 | 0.0120953 |
| 23 | 0.026243 | 355.842 | 0.0120938 |
| 24 | 0.026643 | 360.023 | 0.0120876 |
| 25 | 0.026987 | 360.042 | 0.0120624 |

**Table 6:** Related decision variables for obtained non-dominated solutions.

| Fuzzy Ranking | $P_{\_WT,5}$ [kW] | $P_{\_FC,5}$ [kW] | $P_{\_PV,5}$ [kW] | $P_{\_WT,12}$ [kW] | $P_{\_FC,12}$ [kW] | $P_{\_PV,12}$ [kW] |
|---|---|---|---|---|---|---|
| 1 | 200.20 | 0.000 | 141.52 | 200.43 | 0.000 | 200.0 |
| 2 | 180.41 | 19.60 | 142.63 | 198.25 | 3.600 | 200.0 |
| 3 | 197.85 | 3.630 | 140.93 | 190.34 | 10.00 | 200.0 |
| 4 | 190.03 | 30.02 | 120.83 | 200.42 | 20.00 | 180.7 |
| 5 | 190.87 | 40.42 | 110.22 | 210.32 | 20.33 | 170.6 |
| 6 | 195.44 | 10.82 | 135.83 | 210.12 | 0.000 | 190.6 |
| 7 | 193.38 | 15.82 | 133.05 | 200.45 | 15.23 | 185.3 |
| 8 | 210.82 | 0.000 | 130.87 | 195.12 | 5.542 | 200.0 |
| 9 | 200.35 | 10.62 | 131.94 | 193.67 | 7.861 | 200.2 |
| 10 | 200.86 | 15.52 | 125.96 | 190.87 | 20.73 | 190.3 |
| 11 | 201.28 | 8.261 | 132.72 | 180.54 | 30.43 | 190.8 |
| 12 | 195.89 | 5.191 | 141.50 | 180.34 | 40.43 | 180.7 |
| 13 | 193.25 | 10.39 | 135.72 | 210.65 | 0.000 | 190.8 |
| 14 | 180.90 | 20.52 | 141.52 | 195.76 | 10.32 | 195.3 |
| 15 | 179.26 | 15.24 | 135.62 | 205.32 | 15.64 | 180.3 |
| 16 | 200.24 | 10.86 | 130.94 | 200.41 | 30.24 | 170.1 |
| 17 | 200.52 | 20.97 | 120.83 | 201.41 | 10.35 | 190.9 |
| 18 | 200.64 | 30.42 | 110.73 | 190.83 | 10.35 | 200.0 |
| 19 | 201.26 | 10.96 | 130.73 | 190.34 | 20.98 | 190.7 |
| 20 | 202.68 | 0.000 | 141.51 | 185.43 | 20.60 | 195.1 |
| 21 | 175.29 | 25.42 | 141.57 | 175.43 | 25.73 | 200.0 |
| 22 | 174.77 | 15.63 | 149.55 | 174.33 | 15.43 | 210.8 |
| 23 | 190.32 | 30.83 | 120.23 | 198.45 | 6.860 | 196.6 |
| 24 | 195.41 | 20.53 | 125.53 | 190.13 | 17.54 | 193.4 |
| 25 | 210.22 | 0.000 | 130.95 | 202.41 | 25.13 | 183.2 |

As seen in Table 6 for the best compromising solution with fuzzy ranking 1 which is highlighted in the first row of Table 5. The corresponding normalized membership function is 0.0124843 and related emission is 0.022017 and life cycle cost ($) is 310.0236 ($/h) and related $P_{\_WT,\,5}$ =200.2 [kW], $P_{\_FC,\,5}$ =0 [kW], $P_{\_PV,\,5}$ =141.52 [kW], $P_{\_WT,\,12}$ =200.43 [kW], $P_{\_FC,\,12}$ =0 [kW], $P_{\_PV,\,12}$ =200 [kW].

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*Conclusion:*

This paper deals with environmental protection and environmental impacts reduction of utilization of conventional fossil plants for electricity production. Since these power plants product some pollution gas, e.g. SOx, particulates, CO, CO2 and various unburned or partially burned hydrocarbons, this research investigates the utilization of hybrid clean energy resources including solar energy and wind energy with conventional distributed generation e.g. fuel cell as an alternative instead of fossil power plants. Of course it is expensive enough for electrical engineers to produce electrical power using implantation of wind turbines and photovoltaic cell, but this cost could be moderated by means of fuel cell and other DGs such as microturbines and diesel generators.

On the other hand, these conventional DGs due to fuel consumption, are inserting pollutant gases into atmosphere. Therefore this paper focuses on the optimal sizing the hybrid renewable energy resources combined with fuel cell units as grid connected to support electricity. The total emission reduction and total cost minimization are considered as two conflicting objective functions which optimized using a non dominated sorting approach, NSGAII. At the end of research, to validate the results, the single objective problem based only cost and again based only emission using NSGAII is analyzed and it is compared with other intelligent method e.g. GA and PSO.

## REFERENCES

[1] Faisal, A., Mohamed, Heikki, N. Koivo, 2010. System modelling and online optimal management of Micro-Grid using Mesh Adaptive Direct Search, 32: 398–407.

[2] Taher Niknama, Abdollah Kavousifarda, Sajad Tabatabaei, Jamshid Aghaei, 2011. Optimal operation management of fuel cell/wind/photovoltaic power sources connected to distribution networks. Journal of Power Sources, 196: 8881-8896.

[3] Hernandez-Aramburo, C.A., T.C. Green, N. Mugniot, 2005. Fuel consumption minimization of a micro-Grid. IEEE Trans Ind Appl, 4(3): 673-81.

[4] Basu, M., 2008. Dynamic economic emission dispatch using non dominated sorting genetic algorithm. Int J Electr Power Energy Syst, 30(2):140-9.

[5] Carlson, D.E., 1995. Recent advances in photovoltaics. In: Proceedings of the Intersociety Engineering Conference on Energy Conversion, 621-626.

[6] Kamalapur, G.D., R.Y. Udaykumar, 2011. Rural electrification in India and feasibility of photovoltaic solar home systems. Int J Electr Power Energy Syst, 33: 594-599.

[7] Amin Hajizadeh, Masoud Aliakbar Golkar, 2007. Intelligent power management strategy of hybrid distributed generation system. Int J Electr Power Energy Syst, 29: 783-795.

[8] Chun Che Fung, Waraporn Rattanongphisat, W. Chem Nayar, 2002. A simulation study on the economic aspect of hybrid energy systems for remote islands in Thailand. In: Proceedings. IEEE Region 10 Conference on Computers, Communications, Control and Power Engineering, 3: 1966-1969, 28-31.

[9] Kumar, A., and W. Gao, 2010. Optimal distributed generation location using mixed integer non-linear programming in hybrid electricity markets. IET Gener. Transm. Distrib., 4(2): 281-298.

[10] HOMER Publications, NREL (NationalRenewable Energy Laboratory) available at: https://analysis.nrel.gov/homer/includes/downloads/HOMERPublications.pdf.

[11] Alireza Bagherian, S.M., Moghaddas Tafreshi, 2009. A developed energy management system for a microgrid in the completive electricity market. IEEE Bucharest Power Teach Conference, Bicharest, Romania, Jun 28th -July 2nd, pp: 1-6.

[12] Chandramohan, S., Naresh Atturulu, R.P. Kumudini Devi, B. Venkatesh, 2010. Operating cost minimization of a radial distribution system in a deregulated electricity market through reconfiguration using NSGA method, Int J Electr Power Energy Syst, 32: 126-132.

[13] Mantway, A.H. and Mohammad, M. Al-Muhaini, 2008. Multi-Objective BPSO algorithm for distribution system expansion planning including distributed generation. Transmission and Distribution Conference and Exposition,2008.IEEE/PES,Chicago,IL,21-24April, pp: 1-8.

[14] Azmy, A.M., I. Erlich, 2005. Online optimal management of PEM fuel cells using neural networks. IEEE Trans Power Deliv, 29(2):1051-8.

[15] Orero, S.O., M.R. Irving, 1997. Large scale unit commitment using a hybrid genetic. Int J Electr Power Energy Syst, 19(1):45-55.

[16] Seryasat, O.R., M. Aliyari Shoorehdeli, F. Honarvar, A. Rahmani, 2010. Multi-fault diagnosis of ball bearing using intrinsic mode functions, Hilbert marginal spectrum and multi-class support vector machine, International Conference on Mechanical and Electronics Engineering, (2):145-149.

[17] Seryasat, O.R., M. Aliyari Shoorehdeli, F. Honarvar, A. Rahmani, 2010. Multi-fault diagnosis of ball bearing based on features extracted from time-domain and multi-class support vector machine (MSVM), 11nd IEEE International Conference on Systems, Man, and Cybernetics, 4300-4303.

[18] Seryasat, O.R., M. Aliyari Shoorehdeli, F. Honarvar, A. Rahmani, J. Haddadnia, 2010. Multi-fault diagnosis of ball bearing using intrinsic mode functions, Hilbert marginal spectrum and multi -class support vector machine, 2nd IEEE International Conference on Systems, Man, and Cybernetics, 4300-4303.
[19] Seryasat, O.R., H. Ghayoumi Zadeh, M. Ghane, Z. Abooalizadeh, A. Taherkhani, F. Maleki, 2013. Fault Diagnosis of Ball-bearings Using Principal Component Analysis and Support-Vector Machine, Life Science Journal, 10(1s): 393-397.
[20] Seryasat, O.R., J. Haddadnia, Y. Arabnia, M. Zeinali, Z. Abooalizadeh, A. Taherkhani, S. Tabrizy, F. Maleki, 2012. Intelligent Fault Detection of Ball-bearings Using Artificial neural networks and Support-Vector Machine, Life Science Journal, 9(4): 4186-4189.
[21] Javad Haddadnia, Omid Rahmani Seryasat, Hamidreza Rabiee, 2014. Fault Detection of Induction Motor Ball Bearings, Advances in Environmental Biology, 8(6): 1802-1809.
[22] Seryasat, O.R., M. Habibi, M. Ghane, H. Taherkhani, Fault Detection of Rolling Bearings using Discrete Wavelet Transform and Neural Network of SVM, Advances in Environmental Biology, 8(6): 2175-2183.
[23] Rahmani, O. and A. Taherkhani, 2014. A method of data encryption in NOC, Journal of Applied Science and Agriculture, 9(4): 1903-1906
[24] Javad Haddadnia, Omid Rahmani Seryasat, 2014. Classing images using words package model and fuzzy weighting of the words of the vocabulary, Journal of Applied Science and Agriculture, 9(10): 78-82