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Economics of Distributed Generation Using Particle Swarm Optimization: A Case Study

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Abstract— **The main objective of this paper is to solve the problem of power crises in the world. In present scenario the conventional sources are insufficient to meet our increasing demand. Keeping this in mind I have tried to analyse the advantage of Distributed Generation. In this process of distributed generation I have utilized the developing renewable sources of energy. As the renewable sources like solar & wind power are uncertain. So I have tried to incorporate fuel cell to provide additional backup requirement. For fulfilling the above objectives I have used Particle Swarm Optimization Technique to obtain the optimum value of generation. Further I have compared the output between my program result and Homer Software result. I have also shown the advantage of fuel cell over battery backup.**

Keywords: Distributed Generation; Homer software; Renewable Energy; Hybrid Generation; Particle Swarm Optimization

I. INTRODUCTION

Fossil fuels are a relatively short-term energy source and consequently, the uses of alternative sources such as solar energy are becoming more wide spread.More importantly, these non-renewable energy resources are quickly dwindling and will no longer be available in the near future due to rapid exploitation. Environmental phenomenon, such as global warming and depletion of the ozone layer attributed to emissions from massive fuel combustion are slowly but surely causing widespread problems to every living thing on earth. Renewable energy, particularly photovoltaic technology is one very effective solution available today [1]. Distributed generation is any electricity generating technology installed by a customer or independent electricity producer that is connected at the distribution system level of the electric grid [2]. This includes all generation installed on sites owned and operated by utility customers, like solar photovoltaic serving a house or a cogeneration facility serving an office. It also covers any commercial-scale generation that is connected to the grid at the distribution level, rather than the transmission level. Distributed generation is small-scale power generation technologies (typically in the range of 3 kW to 10 MW) used to provide an alternative to or an enhancement of the traditional electric power system. The usual problem with distributed generators is their high costs but it has low emission of pollution [3].

II. DEFINITIONS

Distributed Generation (DG) is also known as on-site generation, dispersed generation, embedded generation, decentralized generation, etc. It varies from country to country. Over the last century, be it developed nation or developing nation, on account of rapid industrialization causing high rate of growth in the demand for electricity, everyone resorted to establishment of large scale centralized generation facility. The plants concerned were based on use of fossil-fuel (solid, liquid as well as gas), hydro, nuclear elements. Due to the economy of scale with large unit size, it became possible to have big centralized power stations near the sources to deliver power to load centers through the medium of high voltage transmission lines over a long distance. From environment point of view as well due to limitation of natural resources, it is in fact advantageous too to have the plants away from populated areas. Of course like power grid, gas grid has also been constructed that allows use of less polluting natural gas-based plants right at the load center, where it may not be uncommon to have waste heat recovery and use combined cycle plant to achieve higher efficiency and at the same time for heating in winter days, if the need be. On the other hand Distributed Generation too is a method to reckon with, particularly when unbundling of power sector has come up with generation, transmission, and distribution recognized as distinct entities. Low capital investment, local use of generated power by the load, absence of any high voltage transmission system, etc. lead to flurishing of this type of decentralized generation. Advancement of technology with renewable energy sources, gradual reduction in cost, ease of operation and maintainability, etc., all go in favor of Distributed Generation as source of green power. Also if it is not as replacement to centralized large generation, it is at least to supplement the entire effort of generating capacity addition to a great extent. Further in the context of absence of right-of way for drawing new high voltage lines, it is a boon as it envisages connectivity through low voltage networks only and that too over short distance [4].

In UK Distributed Generation is defined [5] as a generation plant that is connected to a distribution network and not to a transmission network. In a similar tone in USA it is referred to as small scale generation of electric power by a unit sited close to the load being served. Both of these justify terming Distributed Generation as embedded to distribution system. However, as per American Council for an Energy Efficient Economy for Distribution Power Generation, its is also known as any technology that produces power outside of the utility, which is in fact the case for this type of generation. Too effectively it means decentralized small scale generation directly supplying load and having interconnection at low voltage with distribution network. Moreover it is very often in the context of electrification of rural areas including remote villages / hamlets [6].

III. BENEFITS OF DISTRIBUTED GENERATION

As mentioned above, basic tangible benefits that may be derived out of such sort of distributed or dispersed or decentralized generation are the following.

- Easy and quicker installation on account of prefabricated standardized components
- Lowering of cost by avoiding long distance high voltage transmission
- Environment friendly where renewable sources are used
- Running cost more or less constant over the period of time with the use of renewable sources
- Possibility of user-operator participation due to lesser complexity

More dependability with simple construction, and consequent easy operation and maintenance Of course the issue of intermittent supply may be a big issue, particularly when backup supply from grid does not exist. Initial cost too may be high depending upon location in a number of cases. [7]

IV. HOMER SOFTWARE

National Renewable Energy Laboratory’s (NREL) Hybrid Optimization Model for Electric Renewable (HOMER) software has been employed to carry out the present study. HOMER performs comparative economic analysis on a distributed generation power systems. Inputs to HOMER will perform an hourly simulation of every possible combination of components entered and rank the systems according to user-specified criteria, such as cost of energy (COE, US$/kWh) or capital costs. Furthermore, HOMER can perform “sensitivity analyses” in which the values of certain parameters (e.g., solar radiation or wind speed) are varied to determine their impact on the system configuration [8].

A. HOMER: Simulation

HOMER simulates the operation of the system based on the components chosen by the designer. In this process, HOMER will perform the energy balance calculation based on the system configuration consisting several numbers and sizes of component. In this case study, PV array system, wind turbine, diesel generator with battery and converter are the components chosen for the analysis. It then determines the best feasible system configuration which can adequately serve the electric demand. HOMER simulates the system based on the estimation of installing cost, replacement cost, operation and maintenance cost, fuel and interest.

B. HOMER: Optimization

The optimization process is done after simulating the entire possible solutions of hybrid renewable energy system configuration. HOMER display a list of configurations sorted based on the Total Net Present Cost (TNPC). It can be used to compare different types of system configuration from the lowest to the highest TNPC. However, the system configuration based TNPC is varied depending to the sensitivity variables that have been chosen by the designer.

C. HOMER: Sensitivity Analysis

The HOMER software will repeat the optimization process for every selection of sensitivity variables for the hybrid renewable energy system. The sensitivity variables are such as the global solar, wind speed and the price of diesel fuel. Then, the list of various configurations of hybrid renewable energy will be tabulated from the lowest to the highest TNPC. The optimal solution of hybrid renewable energy system is referring to the lowest TNPC.

V. SYSTEM DESCRIPTION

On the design point of view, the optimization of the size of hybrid plants is very important, and leads to a good ratio between cost and performances. Before the system sizing, load profile and available insolation should be evaluated. Therefore they are presented in the following sections.

A. Solar Radiation and Wind Speed Data

In the present work, solar radiation and wind speed data represents average of the period 1986-1993, and collected from real case near Kolaghat (Tamluk 22° 18' N 87° 58' E). [9].This data has been analysed to assess utilization of hybrid PV/WG/battery/FC power systems to meet the load requirements of a typical remote village (with annual energy demand average of 623 (kWh/d)).The monthly average daily solar radiation ranges from 3.26 to 7.61 (kWh/m).

B. Load Profile

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An important consideration of any power generating system is load. As a case study and as a representation of remote village which lack access to the utility grid, the measured annual average energy consumption has been considered to scale the load to 623 (kWh/d) in the present study. The daily average load profile is shown in Fig. 3. The peak requirements of the load dictate the system size. In this study 65.1 (kW) has been considered to scale peak load.

VI. RENEWABLE ENERGY

Renewable energy is energy which comes from natural resources such as sunlight, wind, rain, tides, and geothermal heat, which are renewable (naturally replenished). About 16% of global final energy consumption comes from renewable, with 10% coming from traditional biomass, which is mainly used for heating, and 3.4% from hydroelectricity. New renewable (small hydro, modern biomass, wind, solar, geothermal, and biofuels) accounted for another 3% and are growing very rapidly[10] The share of renewable in electricity generation is around 19%, with 16% of global electricity coming from hydroelectricity and 3% from new renewable[11].

VII. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is a self-adaptive global search based optimization technique introduced by Kennedy and Eberhart [8]. The algorithm is similar to other population-based algorithms like Genetic algorithms but, there is no direct re-combination of individuals of the population. Instead, it relies on the social behavior of the particles. In every generation, each particle adjusts its trajectory based on its best position (local best) and the position of the best particle (global best) of the entire population. This concept increases the stochastic nature of the particle and converges quickly to a global minimum with a reasonable good solution. [13]

Particle swarm optimization (PSO) is one of the evolutionary computation techniques. Like the other evolutionary computation techniques, PSO is a population-based search algorithm and is initialized with a population of random solutions, called particles. Unlike in the other evolutionary computation techniques, each particle in PSO is also associated with a velocity. Particles fly through the search space with velocities which are dynamically adjusted according to their historical behaviours. Therefore, the particles have a tendency to fly towards the better and better search area over the course of search process. Since its introduction in 1995 (Kennedy and Eberhart 1995, Eberhart and Kennedy 1995), PSO has attracted a lot of attentions from the researchers around the world. A lot of research results have been reported in the literature.

The original PSO algorithm has been discovered through simplified social model simulation. It is related to the bird flocking, fish schooling, and swarm theory. The PSO was first designed to simulate birds seeking food which is defined as a "cornfield vector." The bird would find food through social cooperation with other birds around it (within its neighbourhood). Particle swarm optimization is initialized with a population of random solutions. Each potential solution is also assigned a randomized velocity, and the potential solutions, called particles, are then "flown" through hyperspace. Each particle keeps track of its coordinates in hyperspace which are associated with the best solution (fitness) it has achieved so far and the value of that fitness is stored. This value is called *pbest.* Another "best" value is also tracked. The "global" version of the particle swarm optimizer keeps track of the overall best value, and its location, obtained thus far by any particle in the population; this is called *gbest.* The particle swarm optimization concept consists of, at each time step, changing the velocity (accelerating) each particle toward its *pbest* and *gbest* (global version). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward *pbest* and *gbest.*

$$Vi^{k+1} = w * v^k + c1 * rand() * (pbesti^k - xi^k) + c2 * rand() (gbest^k - xi^k) \ldots\ldots (1)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \ldots\ldots (2)$$

vi^k : velocity of individual i at iteration k i.e. Vi = (vi1, vi2, … , viD) , the rate of the Position change (velocity) for particle i.

w : weight parameter criteria;

c1 and c2 : acceleration constant;

rand () : uniform random value in the range [0 1];

xi^k : position of individual i at iteration k at D dimensional space. Xi = (xi1, xi2…, xiD)

$Pbesti^k$: best position of individual i at iteration i.e. Pbesti = (pbesti1, pbesti2…, pbestiD) which giving the best fitness value of the i^{th} particle;

$Gbest^k$: best position of the group at iteration k i.e. The index of the best particle among all the Particles in the population

Equation (1) & (2) are the equations describing the flying trajectory of a population of particles. Equation (1) describes how the velocity is dynamically updated and Equation (2) the position update of the "flying" particles. Equation (1) consists of three parts. The first part is the momentum part.

The velocity can't be changed abruptly. It is changed from the current velocity. The second part is the "cognitive" part which represents private thinking of itself - learning from

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its own flying experience. The third part is the "social" part which represents the collaboration among particles - learning from group flying experience (Shi and Eberhart 1998b). In Equation (1), if the sum of the three parts on the right side exceeds a constant value specified by user, then the velocity on that dimension is assigned to be ±Vmax, that is, particles' velocities on each dimension is clamped to a maximum velocity Vmax, which is an important parameter, and originally is the only parameter required to be adjusted by users. Big Vmax has particles have the potential to fly far past good solution areas while a small Vmax has particles have the potential to be trapped into local minima, therefore unable to fly into better solution areas. Usually a fixed constant value is used as the Vmax, but a well designed dynamically changing Vmax might improve the PSO's performance (Fan and Shi 2001). The PSO algorithm is simple in concept, easy to implement and computational efficient. The original procedure for implementing PSO is as follows:

1. Initialize a population of particles with random positions and velocities on D dimensions in the problem space.

2. For each particle, evaluate the desired optimization fitness function in D variables.

3. Compare particle's fitness evaluation with its pbest. If current value is better than pbest, then set pbest equal to the current value, and Pbesti is equals to the current location xi in D-dimensional space.

4. Identify the particle in the neighborhood with the best success so far, and assign its index to the variable gbest.

5. Change the velocity and position of the particle according to Equation (1) and (2).

6. Return to step (2) until a criterion is met, usually a sufficiently good fitness or a maximum number of iterations. Like the other evolutionary algorithms, PSO algorithms is a population based search algorithm with random initialization, and there is interactions among population members. Unlike the other evolutionary algorithms, in PSO, each particle fly through the solution space, and has the ability to remember its previous best position, survives from generation to generation (Shi and Eberhart 2001b) [8]. Furthermore, compared with the other evolutionary algorithms, e.g. evolutionary programming, the original version of PSO is faster in initial convergence while slower in fine tuning (Angeline1998a, 1998b)

A. PSO Algorithm

The PSO definition is presented as follows.

1) Each individual particle ***I*** has the following properties: a current position in search space **X*i***, a current velocity **V*i***, and a personal best position in search space ***yi***.

2) The personal best position y***i***. Corresponds to the position in search space, where particle ***I*** presents the smallest error as determined by the objective function ***f***, assuming a minimization task.

3) The global best position denoted by ***y*** represents the position yielding the lowest error among all the ***yi.*** Equation (1) and (2) define how the *personal* and *global* best values are updated at time, respectively. It is assumed below that the swarm consists of particles.

This, I ∈ 1…s

$$y_i(t+1)=\begin{cases} y_i(t), & \text{if } f(y_i(t) \le f(x_i(t+1))) \\ x_i(t+1), & \text{if } f(y_i(t) > f(x_i(t+1))) \end{cases} \quad (1)$$

$$\hat{y}(t) \in \{y_0(t), y_1(t), \ldots\ldots, \; y_s(t)\} \; f(\hat{y}(t))$$
$$=\min\{f(y_0(t)), \; f(y_1(t)), \ldots\ldots f(y_s(t))\}. \quad (2)$$

During each iteration , every particle in the swarm is updated using (3) and (4). Two

Pseudorandom sequences $r_1 \sim U(0,1)$ and are used to affect the stochastic nature of the $r_2 \sim U(0,1)$ algorithm. For all dimensions j ∈ 1…..n let $x_{i:j}$ $y_{i:j}$, and $v_{i:j}$ be the current position, current personal best position, and velocity of the *i* th dimension of the *i* th particle. The velocity up date step is

$$v_{i,j}(t+1) = \omega v_{i,j}(t) + c_1 r_{1,j}(t)[y_{i,j}(t) - x_{i,j}(t)] + c_2 r_{2,i}(t)[\hat{y}_i(t) - x_{i,j}(t)]. \quad (3)$$

The value of each dimension of every velocity vector v_i, is clamped to the range [-v_{max}, v_{max}] to reduce the likely hood of the particle leaving the search space. The value v_{max} of is usually chosen to be

v_{max} =k*x_{max} where 0.1 ≤ k≤ 1.0

Where x_{max} denotes the domain of the search space. Note that this does not restrict the values of x; to the range

$[-v_{max}, v_{max}]$, rather than that, it merely limits the maximum distance that a particle will move.

The acceleration coefficient C1 & C2 control how far a particle will move in a single iteration. Typically, these are both set to a value of 2.0, although it has been shown that setting C1≠C2 can lead to a good performance [10].

The *inertia weight w* in (3) is used to control the convergence behavior of the PSO. Small values of *w* result in more rapid convergence usually on a sub optimal position, while a too large value may prevent divergence. Typical implementation of the PSO adapts the value of *w* during the training stage, e.g. linearly decreasing it from 1.0 to near 0 over the execution. Convergence can be obtained with fixed values, as shown in [10].

In general, the inertia weight is set according to the following equation:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter_{max}} \cdot$$

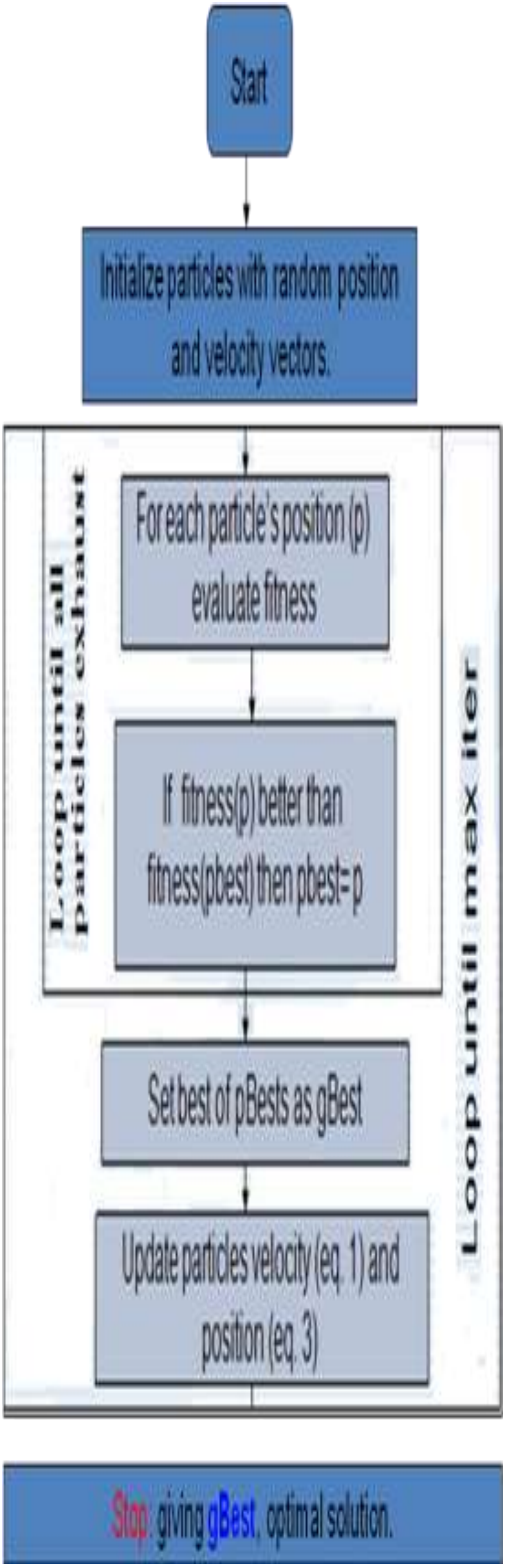
Where the maximum is number of iterations, and is the current iteration number.
The PSO system combines two models: a social-only mode land the cognition-only model [10]. These models are represented by the velocity update, shown in (3). The second term in the velocity update equation $c_1 r_{1,j(t)} [y_{i,j(t)} - x_{i,j}(t)]$, is associated with cognition since it only takes into account the particle sown experiences. The third terms in the velocity update equation

$$c_2 r_{2,j(t)} [y_{j(t)} - x_{i,j}(t)]$$

represents the social interaction between the particles. It suggests that individuals ignore their own experience and adjust their behaviour according to the successful beliefs of individuals in the neighborhood. References [9]

Present a useful dictionary about PSO. The next section is meant to illustrate how this method may be applied in a sample power system. The objective function is the loss reduction. An illustrative numerical example of this technique is carried out in the appendix. The next section is devoted to present some important modification in the algorithm.

A. Flowchart Depicting General POS Algorithm:



VIII. EXPARIMENTAL OUTPUT

```
***************GENERATION UNIT SIZING AND COST ANALYSIS OF WIND-PV-BIOMASS GENERATION***************

 IF YOU ENTER DATA PRESS 1

 IF YOU IMPORT DATA PRESS 2
2

IMPORTED DATA ARE AS FOLLOWING

  HOUR                  LOAD DEMAND          INSOLATION            WINDSPEED
 0:00-- 1:00               84.520              0.000                 4.5
 1:00-- 2:00               69.340              0.000                 4.3
 2:00-- 3:00               59.470              0.000                 4.3
 3:00-- 4:00               59.470              0.000                 4.4
 4:00-- 5:00               59.470              0.000                 4.4
 5:00-- 6:00               56.720              0.000                 4.5
 6:00-- 7:00               60.760              0.340                 4.3
 7:00-- 8:00               102.030              0.380                 4.2
 8:00-- 9:00               315.590              0.410                 4.5
 9:00--10:00               312.220              0.570                 4.8
10:00--11:00               315.570              0.680                 5.3
11:00--12:00               180.260              0.790                 5.8
12:00--13:00               141.270              0.840                 6.0
13:00--14:00               253.790              0.960                 6.3
14:00--15:00               257.140              0.840                 6.5
15:00--16:00               257.140              0.760                 6.5
16:00--17:00               179.860              0.670                 6.3
17:00--18:00               203.930              0.430                 6.0
18:00--19:00               236.630              0.000                 5.6
19:00--20:00               224.800              0.000                 4.8
20:00--21:00               139.370              0.000                 4.8
21:00--22:00               139.370              0.000                 4.7
22:00--23:00               142.170              0.000                 4.6
23:00--24:00               134.710              0.000                 4.5
*********************SIZING OF WIND/PV/FUEL CELL GENERATION SYSTEM**************************


WIND TURBINE         SOLAR PANEL

13                    828
Economic Load sharing among the Wind,PV,FUEL CELL are calculated to be as follows :
669.53                630.53                     2685.502


Cost per Unit:    0.2802



No of Iteration    120

TOTAL DEMAND     TOTAL GENERATION          WIND GENERATION    PV GENERATION        FUEL CELL GENERATION

3985.60              3985.56                     669.531              630.53               2685.50
>> |
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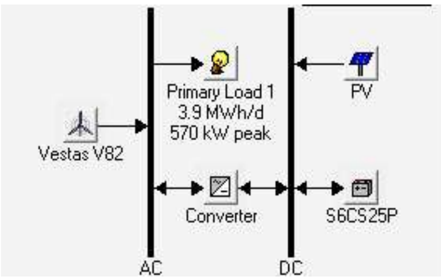
A. Experimental Design

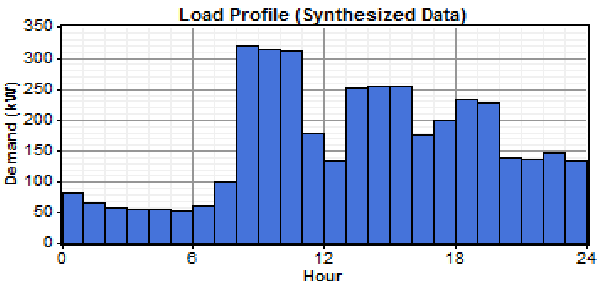
This is the experimental set up design for hybrid generation using HOMAR software.



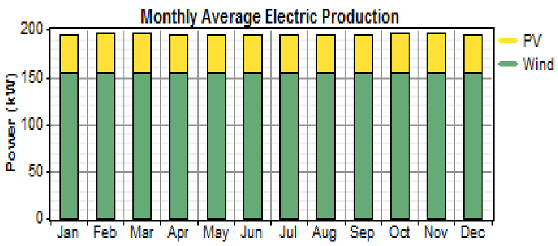
B. Experimental Observation

This is the use load profile data

- **Load Profile:**

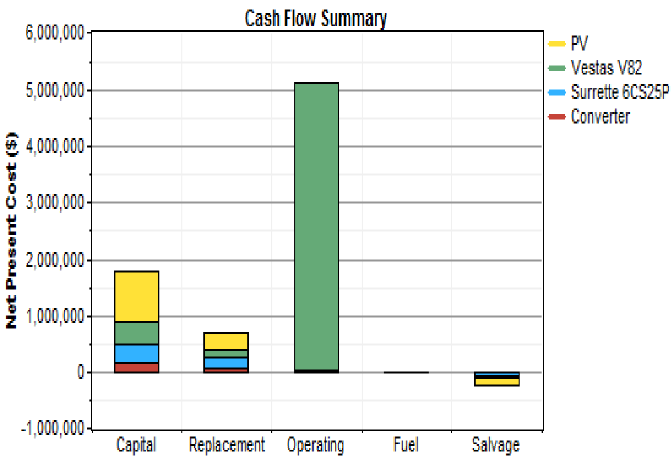


C. Avg. Electric Energy Production



D.Cash Flow Diagram

Cash flow diagram for the all the energy component



PV Array	450 kW
Wind turbine	1 Vestas V82
Battery	450 Surrette 6CS25P
Inverter	400 kW
Rectifier	400 kW
PV Array	450 kW
Wind turbine	1 Vestas V82
Battery	450 Surrette 6CS25P
Inverter	400 kW
Rectifier	400 kW

E. Systems Architecture:

System Architecture feature related data

F. Production of Electrical Energy:

Production of electrical energy for above diagram

Component	Production (kWh/yr)	Fraction
PV array	357,012	21%
Wind turbine	1,352,997	79%
Total	1,710,009	100%

G. Cost summary:

Total net present cost	$ 7,326,370
Levelized cost of energy	$ 0.402/kWh
Operating cost	$ 434,234/yr

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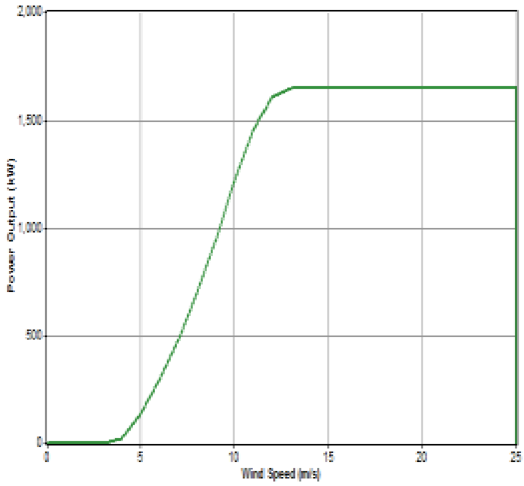
H. Battery Details:

Nominal capacity	1156 Ah
Nominal Voltage	6 V
Max. Capacity	1163 Ah
Life	12 yrs

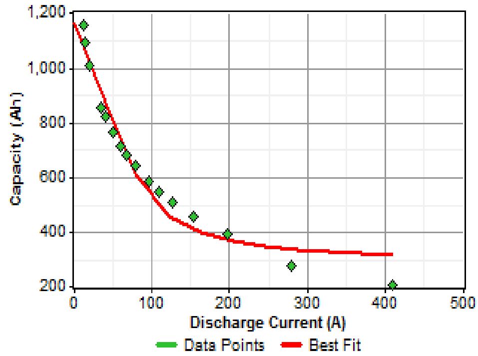
I. PV Details:

Quantity	Value	Units
Rated capacity	450	kW
Mean output	40.8	kW
Mean output	978	kWh/d
Capacity factor	9.06	%
Total production	357,012	kWh/yr

J. Power Curve:



K. Capacity Curve of Battery:



IX. PSO PROGRAM SPECIFICATION

- **SOLAR PANEL:**

Solar panel unit rated- 120 watt
Solar efficiency- 0.12
Solar panel area- 1.07 m^2
Solar panel cost- 614$/panel
Solar panel BOS- 50%

- **WIND TURBINE:**

Wind turbine unit rated- 10000 watt
Wind turbine cut in velocity- 2.5 m/s
Wind turbine cutout velocity- 13 m/s
Wind turbine rated velocity- 11 m/s
Wind turbine cost- 27000$
Wind turbine BOS- 25%

- **FUEL CELL:**

Fixed cost- 3, 50,000$
Hydrogen cost- 12$/kg

X. COMPARITIVE STUDY

HOMER	PARTICLE SWARM OPTIMIZATION
1. Per unit cost of electricity- 0.402$/KWHr.	1. Per unit cost of electricity- 0.2802$/KWHr.
2. System component-wind turbine, photovoltaic cell, battery bank, converter.	2. System component-wind turbine, photovoltaic cell, fuel cell generator
3.Load sharing- Wind Turbine-79% PV Array -21%	3.Load sharing-Wind Turbine -29.62% PV array -28.35% Fuel cell -42.03%

XI. CONCLUSION

In this paper I have tried to find a solution to the problem of conventional energy and their limited resources. Here I have used P-V array, WIND TURBINE and BIOMASS GENERATOR to supply an average load of 3.9 MWHr daily with a peak of 570 KW.

The per unit cost of electricity is 0.3056$/KWHr. This is an optimized result and its practical implementation is constrained by the climatic condition of the area where the project is implemented. In the earlier semester we have used the same load for generation using P-V array, WIND TURBINE and BATTERY BANK through HOMER SOFTWARE. There the cost of electricity was 0.402$/KWHr. I have also considered the aspect of comparative study of the two methods of optimization. I have found out that the cost of electricity is 0.0964$/KWHr less if I use PARTICLE SWARM OPTMIZATION technique. The initial capital cost may be a little high but the main advantage of this kind of generation is that the running cost is very less. The maintenance required is also less due to the absence of moving part in P-V array. The pollution due to distributed generation using renewable sources is negligible. There is absence of harmful emission as well as sewage and solid waste. This increases the compatibility with the environment. The use of distributed generation using renewable sources is being implemented in different parts of the world. I hope that there will be large scale implementation in our country also and our dependency on conventional sources will be reduced.

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