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# An optimized Energy Cost Analysis using Fuzzy Logic Control Algorithm for the autonomous Microgrid

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**Abstract.** In this paper, the significance of Fuzzy Logic Control Algorithm is proposed for determining the effective cost analysis of power generation with respect to the load demand in microgrids. There are many conventional algorithms are developed in the past to evaluate the cost analysis with system constraints, however, they are complex and time consumed. Also, these algorithms are mainly used for conventional systems and are not suitable for microgrids. To overcome these disadvantages, a simple Fuzzy Logic Control Algorithm is used to define the cost analysis effectively. The features of these algorithms are easily adapted and incorporated with the objectives of Demand Side Management strategies in microgrids. In addition, the correlation and an Artificial Bee Colony Optimization technique is proposed between the variables of PV and Wind turbine to obtain the highly accurate power generation samples with respect to the load demands. The analysis of optimization and Fuzzy algorithms are developed using MATLAB Simulation software and the cost analysis are shown for different load variations.

## 1. Introduction

The power sector has seen a lot of transformations to deal with the needs of new technological developments, specifically, the change is from conventional power systems to smart grid system. The increase in global energy demand is the main reason for the deployment of renewables and made an initiative to the development of microgrid and hybrid microgrids. The main challenges are found in the development of microgrids are : Energy management, Distributed Energy Resources (DER), Energy Storage Sources (ESS), Reactive power management, Microgrid Central controllers, Demand response and Demand side management. In addition, due to lack of standards, policies and awareness between the utilities, prosumer and consumers, the evaluation of energy cost with the Distributed generation in microgrid is another important concern for the data experts.

Data analytics can empower the power system engineers to make data driven decisions, gain better access, fair price markets and be instrumental in addressing challenges of low energy production [1]. From the developing countries like India, the energy consumption has been tripled since 2000 and expected to increase to another level by 2025. Moreover the Indian government is encouraging to use more renewable resources and reduced the infrastructure cost



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on Solar PVs as compare to 2010 statistics. Another challenge is to develop the microgrids based on Distributed generations, energy storage systems and communication systems. Also during peak hours, the real time control system provides an option to integrate with neighborhood microgrids for sharing the active power. The data from DERs plays a vital role in understanding the blocks of power systems for regulating the loads at any time. Based on the geographic location, the characteristics of solar irradiation and wind velocities varies from time to time or intermittent in nature, and it is necessary to investigate these datas indepedently [2].

With the characteristics of load demands, the allocation of DER, ESS and an optional utility plays an important role in developing the microgrid. In addition, another interesting technology from Electric Vechile (EV) known as V-2-X or X-2-V (Vehicle-2-Grid, Grid-2-Vehicle, Vehicle-2-Home) are showing great features in microgrids. Also, the data on load clustering, whether forecasting and prediction and Neighbourhood microgrids are necessary to fix the cost of energy by the aggrgators or virtual Power Player (VPP) through clodcomputing. With the data analytics of solar data and wind data, the consumer will have option to choose the energy from renewables to the load demand or may shift the load to non peak hours, thus achieving the Demand Side Management (DSM) objectives. The data analytic mapping for microgrids is shown in Figure.1 with various components.

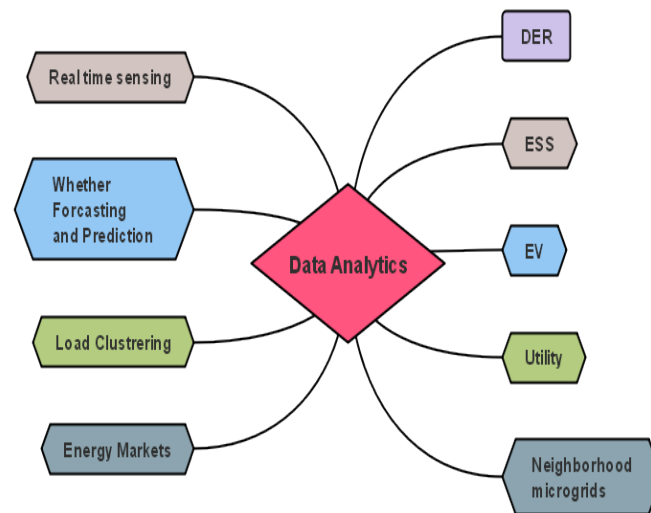


Figure 1: Data Analytic Mapping for Microgrid

The optimazation tools are useful in understaing the constarins of the application and easy to generate the mathematical models. Many optimization techniques are found from in last two decades and used for engineering, social sciences and business management fields. Some nature inspired and meta heuristic optimizations are popular in managing the constraints and easy to resolve the uncertainties. From [3], the optimization technique known as Bacterial Foraging (BF) used for operation and maintainance of microgrid. In [4], the Interior Search Algorithm (ISA) is used for Energy management in microgrids and in [5, 6, 7], the Simulated Annealing (SA), Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are used for Energy Resource Management with various constaints on Electric vehicles and on microgrids.

In this paper, an Artificial Bee Colony Optimization (ABCO) algorithm is used for selecting the highly accurated power generation samples to minimize the requirement of ESS. This ABCO is found to be superior than PSO in the performance and fast convergence [8].

In this paper, the system configuration with the description of Artificial Bee Colony Optimization algorithm and the FLCA is presented in section-II followed by simulation model

and results with conclusion in section III.

## 2. SYSTEM DESCRIPTION

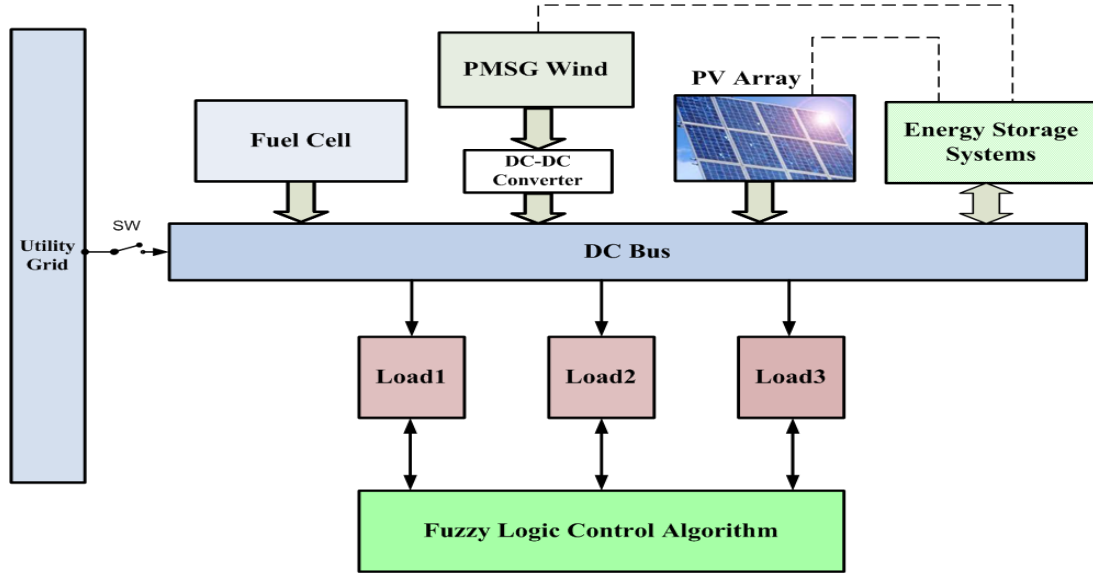


Figure 2: Proposed Microgrid System with FLCA

The various DERs are integrated with the local loads and utility through a Static switch SW, the overall control of the microgrid is achieved with a Local Control, LC and Microgrid Central Control, MGCC, with a proper communication system under different modes of operation, defined as per IEEE 1547 standards. A simple microgrid with DER and loads is shown in Figure.2.

### 2.1. Power generation in microgrid

Most of the generic microgrids consists of Solar energy systems, Wind power systems, Microturbines, Fuel cells and Energy storage systems with their local controls and Microgrid central controls [9, 10]. In this paper, only three local sources of the microgrid are considered for simplicity, they are Fuel cells, Solar Energy system and Wind Energy system as shown in the Figure.3 and its mathematical expressions are as follows:

- **Fuel Cell:** The cost of fuel cell is considered as follows:

$$C_1(P_{FC}(t)) = \alpha_{FC} + \beta_{FC}P_{FC}(t) + \gamma_{FC}P_{FC}^2(t) \quad (1)$$

where  $\alpha_{FC}$ ,  $\beta_{FC}$  and  $\gamma_{FC}$  are the cost coefficients of the Fuel Cells,  $P_{FC}$  is the power capacity of the Fuel Cells and  $C_1$  is the fuel cost of the Cells.

- **Solar Energy System:** Solar power can be expressed from the solar radiation with a constant temperature.

$$P_{PV} = P_{STC} \frac{G_{ING}}{G_{STC}} (1 + k(T_C - T_\gamma)) \quad (2)$$

where  $P_{PV}$  is the generation of power,  $G_{ING}$  is solar irradiance,  $P_{STC}$  is maximum power yield at standard test condition,  $G_{STC}$  is irradiance under standard test condition,  $k$  is the temperature coefficient,

- **Wind Energy System:** The wind power is extracted from the following equation, considering the wind speed is the variable.

$$P_{WT} = \frac{1}{2} \rho \pi R^2 V^3 C_p \quad (3)$$

where  $P_{PV}$  is the generation of power,  $\rho$  is the air density,  $R$  is the radius,  $v$  is the wind velocity of power generation area and  $C_p$  is conversion efficiency of the wind power.

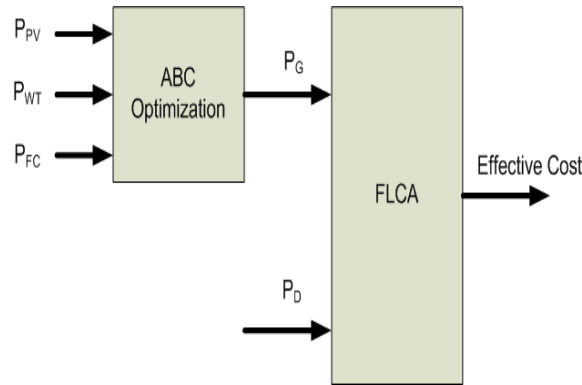


Figure 3: Fuzzy Logic Control Block

### 2.2. Variable demands, $P_D$

Based on demand response characteristics, only three types of demands are considered for this analysis, they are Critical demands,  $P_{DCr}$  Controllable demands,  $P_{CO}$  and Price sensitive demands,  $P_{DPS}$ . The overall mathematical expression for  $P_D$  is as follows:

$$P_D = P_{DCr} + P_{CO} + P_{DPS} \quad (4)$$

### 2.3. Correlation coefficient

Correlation between the power generation from PV and wind are to considered to measure the correlation coefficient at all the various of sun's irradiances and wind speeds. This correlation coefficient measures the perfect match between the power generation variables and it ranges from  $-1$  to  $+1$ . A perfect correlation is said to be  $0$  to  $+1$  or, the power generation variables are matched with the desired load demand and not required any of Energy Storage Sources (ESS), thus the cost of energy is minimum. If the coefficient is  $-1$ , the power generation variables are not matched and the ESS is heavily required to supply to the load with high energy cost. The coefficient is calculated with a popular Spearman's rank correlation coefficient or Spearman's  $\rho$  [11, 12], the equation is as follows:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n-1)^2} \quad (5)$$

where,  $\rho$  is the Spearman's rank correlation coefficient,  $d_i$  is difference between the two ranks of each observation,  $n$  is number of observations.

#### 2.4. Artificial Bee Colony Optimization

The Artificial Bee Colony Optimization (ABCO) algorithm is popular in most of the engineering, social sciences and business management fields. This ABCO consists of three phases for identifying the optimized food source, namely, Employed bee phase, Onlooker bee phase and Scout bee phase. To achieve better solution, this algorithm has an independent objective function and fitness function and is not seen in other popular optimizations techniques [13, 14].

##### *Employed bee phase*

The bees will identify the better food source that already associated with it and generates a new solution. Finally a greedy selection will perform in comparison with current solution.

##### *Onlooker bee phase*

The bees identify food source with a probability of nectar availability and performs a greedy selection in comparison with current solution.

##### *Scout bee phase*

In this phase the exhausted food source is abandoned and generates a new solution.

The ABCO is shown in algorithm 1, it is observed that, from all the phases, a better solution with higher fitness value will have higher probability. Here the analogy of food source is said to be energy sources from renewables.

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#### **Algorithm 1** Artificial Bee Colony Optimization

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- 1: Inputs are objective function, fitness function, lower limit, upper limit,  $N_p$ , Iteration count (T), and limit.
  - 2: Initialize a random population, P.
  - 3: Evaluate objective function,  $f$ , and fitness,  $fit$
  - 4: Set the trial counter of all the food sources equal to zero.
  - 5: **for**  $t = 1$  to T **do**
  - 6:     Perform *Employed bee phase* on all the food sources.
  - 7:     Determine the probability of each food source and perform *Onlooker bee phase* to generate the new food sources with greedy selection.
  - 8:     Perform the *Scout bee phase* of exhausted food sources for a new solution.
  - 9: **end for**
- 

#### 2.5. Fuzzy Logic Control Algorithm

The Fuzzy logic designer [15] is used to evaluate the effective cost per unit for the inputs of power generation(MW), power demand(MW) and effective cost as output. The Figure.4a represents the linear power is generated with linear load variations are considered for testing, similarly, the Figure.4b represents the power is generated with random load variations are considered for testing. The following member functions are considered for power generation(MW), power demand(MW) and effective cost as output along with the rules table are shown Figures 6a, 6b and 7 respectively.

The triangular membership function is considered for evaluating the effective cost of the energy at the output is shown in the Figure 5, it is defined mathematically as follows :

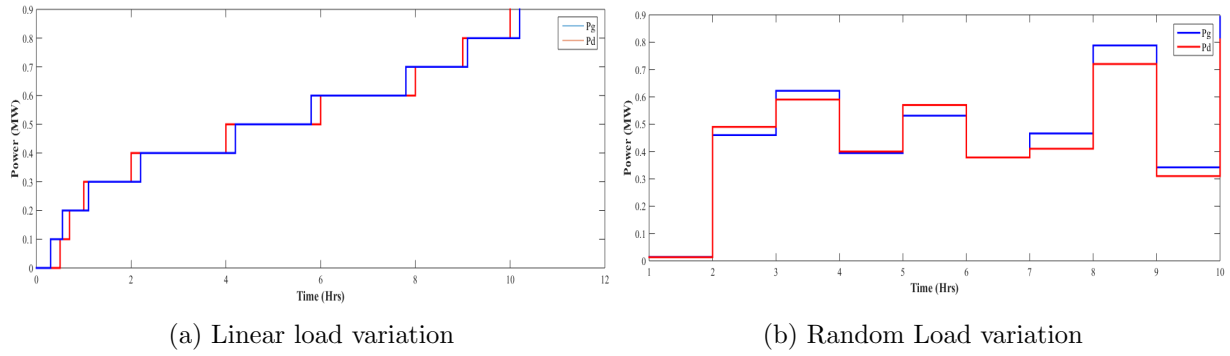


Figure 4: variation of loads for testing

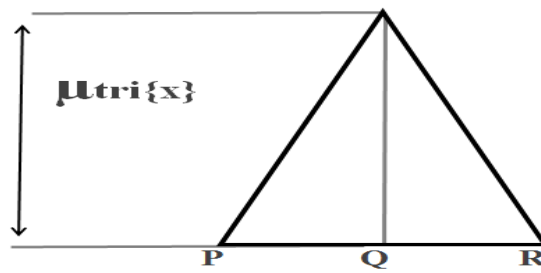
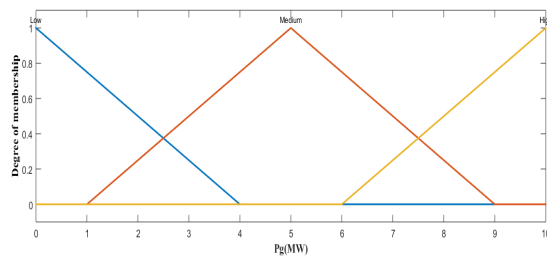
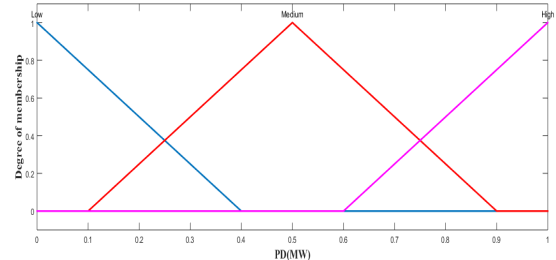


Figure 5: Basic Triangular Membership function

$$\mu_{tri}\{x\} = \max \begin{cases} 0 & \text{if } x \leq P \\ \frac{x-P}{Q-P} & \text{if } P \leq x \leq Q \\ \frac{R-x}{R-Q} & \text{if } Q \leq x \leq R \\ 0 & \text{if } x \geq R \end{cases} \quad (6)$$



(a) Membership function for Pg



(b) Membership function for Pd

Figure 6: Membership functions (Inputs)

The membership rules are defined for various inputs and the corresponding outputs with notations Low (L), Medium (M) and High (H) are derived for the following Table 1, however, the

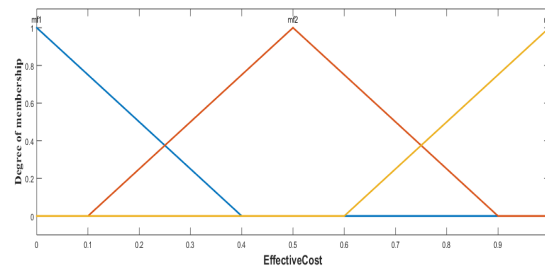


Figure 7: Membership function for Effective cost (Outputs)

customized membership rules can also be developed based on the conditions.

Table 1: Membership Rules

Pg	Pd		
	L	M	H
L	L	M	M
M	L	M	M
H	M	M	M

### 3. Conclusion

Based on the available energy resources from renewable, a correlation is evaluated with Spearman's rank correlation coefficient between the solar PV and wind turbine variables. The coefficient determines the perfect match with the load and thus, defines the usage of the Energy Storage Elements and higher the coefficient, lesser is the energy cost and reduced the usage of ESS and vice versa. The Artificial Bee Colony Optimization algorithm allows us to select the highly accurate power generation samples to minimize the cost per unit with respect to load demand. Finally, the Fuzzy Logic algorithm based on the various membership rules helps us to evaluate the energy cost per unit. However, the system further is improved with the objectives of the Demand Side Management, and will be more reliable and economical with the development of Blockchain Technology in energy sector.

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