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Demand respond-based optimization model for smart grid considering energy storage set-up using firefly algorithm

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Abstract

This paper presents a demand response-based optimization model for reducing the degree of network instability in smart electric grids with a special attention on the energy storage facility. In this paper, the economic distributed generators on a demand-by-the-hour basis as well as optimal battery dimension is estimated. The approach is based on the novel theory for smart grid optimization. Energy Storage Networks (ESNs) are used to develop a range of Demand Response (DR) solutions to help a region achieve optimum resource demand side management. A concept is presented to determine the maximum Battery-Based Energy Storage System (BBESS) feature to be installed in an electrical grid. The Fire Fly Algorithm (FFA) is then explored to plan the economic scheduling of the battery size. A Mixed Integer Linear Programming (MILP) problem is formulated for sizing the PV/wind turbine to BBESS optimally and both problems are solved with General Algebraic Modeling System (GAMS).

Keywords: smart grid, MILP, demand response, firefly algorithm, BBESS

Introduction

In essence, Smart-Grid (SG) is a vision that incorporates transmission networks, transmission grids and multiple energy sources efficiently. To accomplish this integration, Smart Grid employs automated substation & management system, frequency monitoring software and digital sensors. Global electrical energy demand is increasing rapidly, and today's key issue is how to satisfy potential oil demands. The world electricity market will rise rapidly on long-term forecasts [1].

Recently, renewable energy choices have grown to include the electric grid. Many of them are small, localized units and electricity grid interfaces of different sizes. This intrusion will endanger the stability of the power grid, as its unpredictable production will create a supply-demand mismatch. The SG is characterized with the ability to effectively distribute electric energy as well as adapting to wide-ranging situations and incidents by using modern information technology. Furthermore, through correct strategies, the SG has the ability to respond to various events occurring in any part of the system elements, such as generation, transmission, distribution as well as power usage. A typical example is when there exists an interruption of a medium distribution voltage within the grid system, the direction of power-flow within the grid may be automatically changed by the SG such that the power delivery service is recovered. As such, the key aim of smart grid is, therefore, to increase customer satisfaction and decisions to build the operating environment in which consumers and utilities can connect [2, 3, 4].

The smart grid uses modern technologies to enhance the stability, protection and performance of the electrical network from large-scale generation and transmission systems to users of energy and a growing number of distributed and storage services [2]. The transition to an efficient energy grid is one of the key goals in Smart-grid [5]. The use of flexible information management systems ensures quality of energy as unpredictable demands and renewable resources are controlled. The energy demand management EDM (also called Demand-Side Response DSR) involves all measures that seek to adjust the consumer's demand profile in time or /and form to balance supply, and to ensure the efficiency of the use of renewable energy resources [6]. In addition, EDM can be used to promote incorporation of the distributed generation, which can produce substantial energy and transmission savings [7]. Other benefits of EDM include removing blackouts, reducing operating costs and reducing CO2 emissions [8].

SGs deliver many advantageous features, including: bidirectional communication, automated controls, electronic sensors, and micro grids. In order to satisfy the increasing demand for energy, improvements must be made to the output, distribution and consumption. The electricity industry, which has an asset worth over trillions of dollars, is one of the largest industries in the USA. The US operates more than 3.273 services and supports more than 144 million consumers with electricity [9].

Significant contributions have been made in the optimization of energy demand response using different methodologies in the open literature. For instance, the authors of [2] proposed a users' load model as well as the Interior Point technique (IPT). The aim of the study was to reduce the price of electricity and the cost of batteries under conditions of limitation. The IPT as well as the Genetic Algorithm are applied to model a 24-hour power consumption cycle of customers. The solution provided by this optimization approaches reduced the cost of electricity and batteries significantly. This is in accordance with the study carried out by the authors of [3] such that if the price is lowered to minimize the overall price of power, the power consumption in the maximum loading cycle can be moved to other intervals.

Providing an efficient solution for solving the problem of uncertainties associated with the hybrid PV/wind considering BBESS is a complex optimization problem and various approaches have been presented to solving this problem in the open literature.

Figure 1 below is one of the effective approaches proposed for solving this problem through the use of Simulating Annealing (SA); an algorithm used to optimize the battery storage capacity of an interconnected PV/wind power system [4]. The main bottleneck associated with this technique is that the unit costs to aid resources and other elements are inflationary, which has a greater influence on the optimal overall cost and share of investment cost with the complex auxiliary energy unit cost.

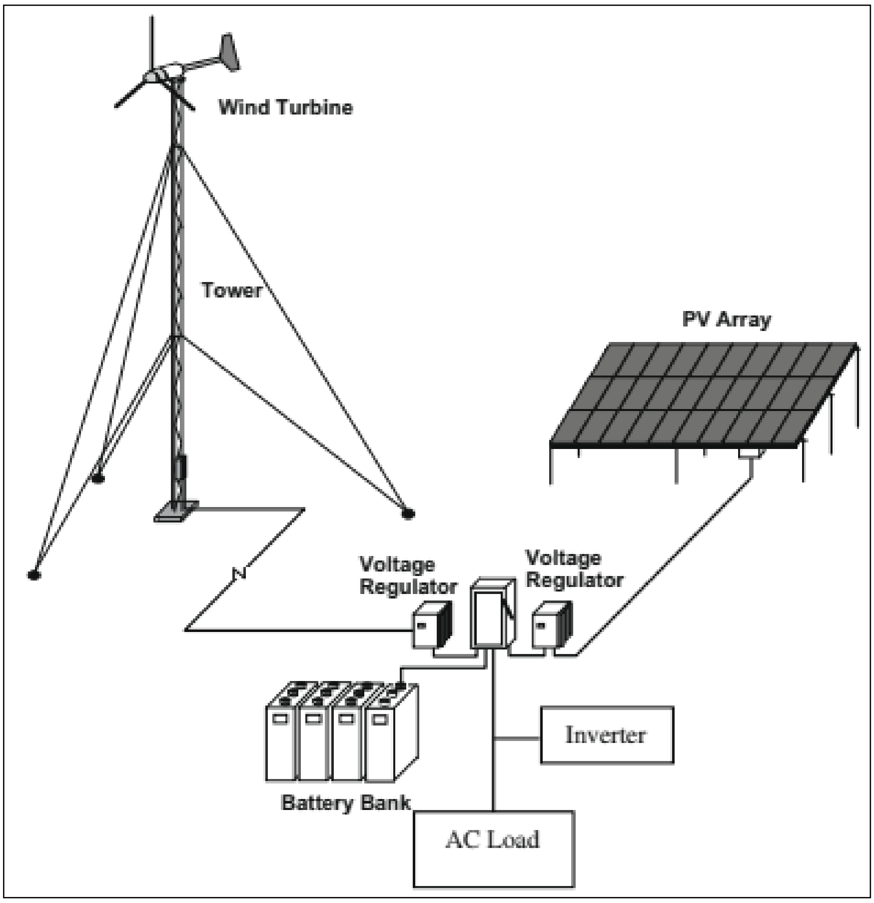

Fig 1: A fundamental hybrid energy system schematic diagram [4]

This paper, therefore, presents an alternative method for optimizing the demand response in an electric system considering the energy storage facility using FireFly Algorithm (FFA) for planning the economic scheduling of the battery size.

Materials and Method

The capital cost of the battery is an important factor when measuring the battery size. By reducing the overall cost per day during the regular schedule for microgrids and BBESS, the ideal BBESS size is attained. The objective of the microgrid is thus the total operating costs caused by the following conditions:

$$\mathrm{OC} = \mathrm{SC_D} + \mathrm{TCPD_{BBESS}} \tag{1}$$

$$\mathrm{SC_D} = \mathrm{Min} \sum_{t=1}^{T} \left(\sum_{t=1}^{N} F_i(P_{d;gen}(t)) \right) + C_{batt} \tag{2}$$

$$\mathrm{TCPD_{BBESS}} = \left(\mathrm{CRF} \times C_{batt;max} + \frac{\mathrm{MC}}{365} \right) \times E_{batt} \tag{3}$$

The costs of the day's planning are based on the total of three diesel generators transported to meet the load requirement and the battery stock charging/unloading costs. In the analysis, the period T is formulated as 24 hours, while N is taken as three.

Battery Storage Model

The charge-discharge cost of battery at any time interval represented as a function of battery power and Dept of Discharge (DOD) is formulated in Equation (6) [5, 6]. The cost function of the battery storage during charge-discharge event can be expressed as

$$Co_{batt}(t) = \frac{Co_{batt.max} \times P_{batt} \times \Delta_t}{E_{batt} \times I_c(DOD_{batt}(t)) \times \eta_{batt}^2} \tag{4}$$

$$I_c(DOD_{batt}(t)) = 694 \times (DOD_{batt}(t))^{-0.795} \tag{5}$$

$$DOD_{batt}(t) = 1 - SOC_{batt}(t) \tag{6}$$

The state of charge (SOC) denotes the battery capacity status; given as:

$$SOC_{batt}(t+1) = SOC_{batt}(t) - \frac{P_{batt.chg}(t) \times \Delta_t \times \eta_{batt}^{chg}}{E_{batt}} - \frac{P_{batt.dchg}(t) \times \Delta_t}{E_{batt} \times \eta_{batt}^{dchg}} \tag{7}$$

one-hour time interval is denoted as Δ_t;
Battery charging (η_{batt}^{chg}), and discharging (η_{batt}^{dchg}) in this paper are considered similar and equivalent to battery efficiency.

Photovoltaic Solar Model

The measurement power of the solar photovoltaic range relies on the sunshine and environmental temperature every hour [7]. The energy of the PV can be modelled as

$$P_{pv,out} = P_{pv,rated} \times \frac{I}{I_{ref}} \times [1 + K_t\{(T_{amb} + (0.0256 \times 1)) - T_{ref}\}] \tag{8}$$

The cost of solar photovoltaic energy depends on the initial costs and performance, which is usually specified as

$$C_{pv} = (\textstyle\sum_{t=1}^{T} P_{pv,out}\,(t)) \times IC_{pc} \times CRF \tag{9}$$

Results and Discussion

In this research the efficiency of the proposed energy management strategies is demonstrated by a usually low-voltage micro-grid with a Li-ion battery. The photovoltaic micro-grid is 68 kW and the wind turbine system is 38 kW. An idea was taken of the expense of the battery capital, operating costs, interest rates and lifespan from [8].

Scenario 1: Renewables and Load-Functioning

Fig. 1 displays the micro-grid load demand and graphs for renewable energy output. In most cases, the demand for load is greater than the output of solar.

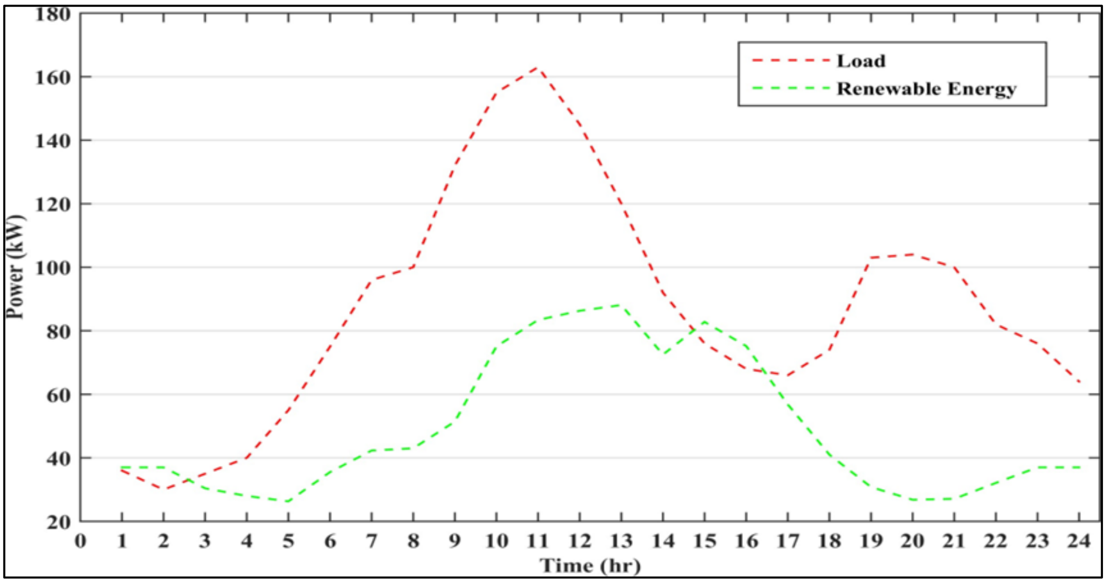

Fig 2: Data for a day on the renewable technology and load

Scenario 2: An Effective Battery Size is Introduced to the Setup

An efficient device is calculated to generate an optimized battery size for the micro-grid as shown in Fig. 3. The algorithm calculates the best battery capacity to reduce the OC of the micro-grid. The optimum size operating costs are ₦162, 810. For 100 kWh - 250 kWh, a phase size of 15 kWh has been measured in the micro-grid OC in order to verify the outcome of the proposed process, considering all the limitations of the energy resources and the battery distribution.

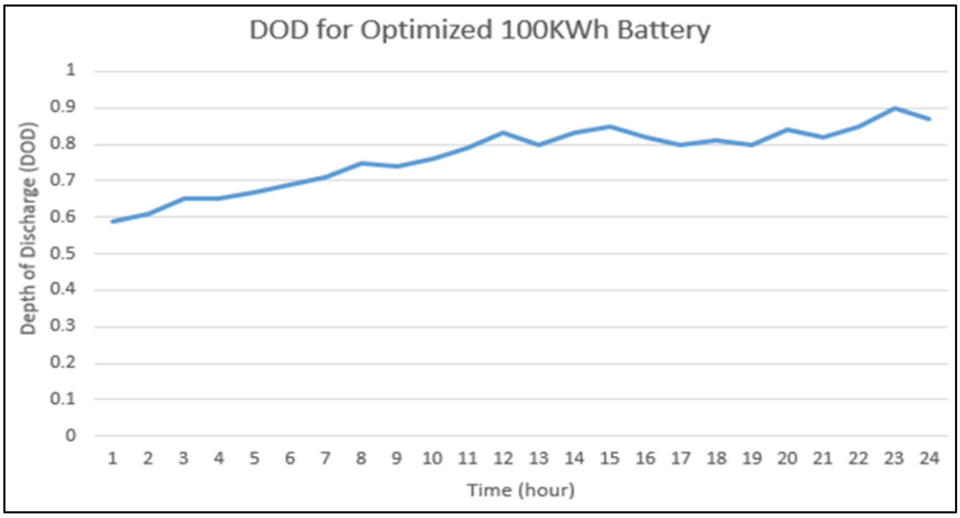

Fig 3: DOD condition for the optimized battery

It can be seen from Fig. 3 that the battery discharges in the first few hours with a growing DOD. At 6:00 am, the DOD battery increased to 38 percent and the battery cost increased as the generator discharges additional power.

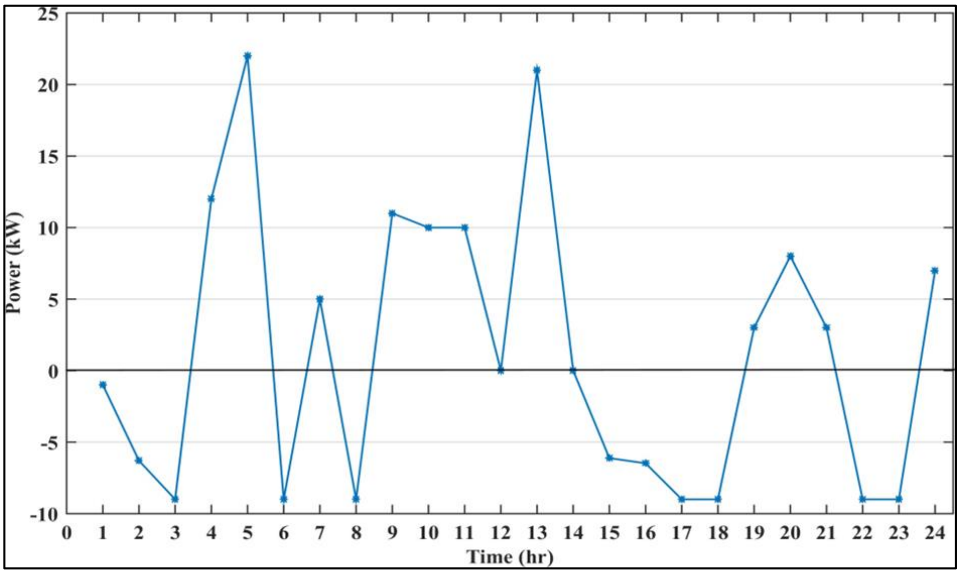

Fig 4: Battery charging/discharging evaluation

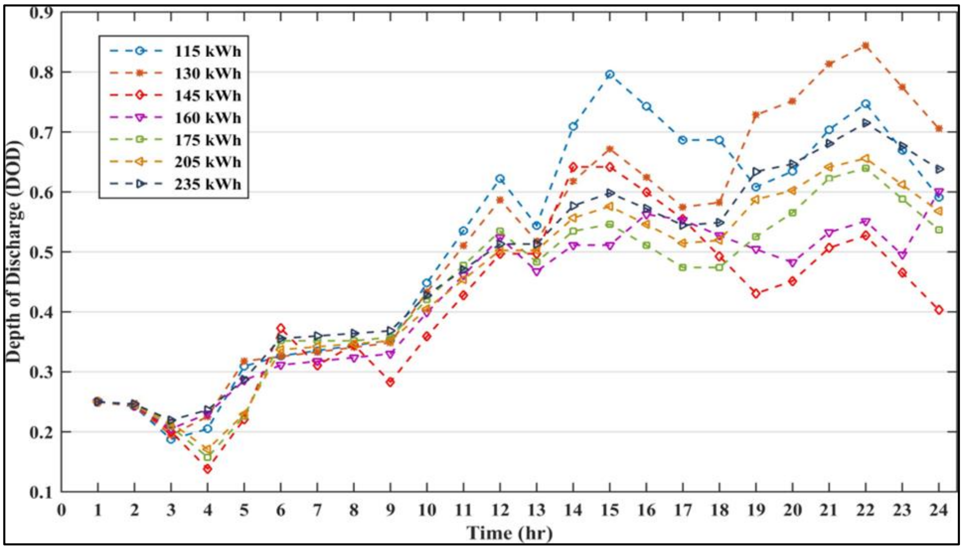

Fig 5: DOD battery curves for various sizes

The battery charging is one of the benefits of the system when the DOD level is greater, so that the battery isn't really drained during critical periods. To tackle the economic shipment issues and battery size, a firefly optimization algorithm was introduced.

Conclusion

With the forecast of more electricity supply using renewable energy sources, economic and battery-size energy storage to maintain a steady service in the insulated micro grid, elements should be considered. With the real time battery depletion costs, the present study resolved the problem of economic schedules between diesel generators and the stored battery. A large size of BBESS does not reduce the operational expense. For the optimum power configuration of PV and BBESS, GAMS was used to solve a formulated (MINLP) problem with the objective of minimizing annual full costs.

In helping and assisting independent service providers in efficient conduct of rural electrification and extending battery life, I recommend that the energy schedule method proposed should be examined further as a guideline.

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