SMART GRID COST OPTIMIZATION USING GENETIC ALGORITHM

Gundi Anny Mary[1], R.Rajarajeswari[2]

[1]*M. Tech Student, Electrical and Electronics Engineering, SRM University, Chennai*
[2]*Assistant Professor, Electrical and Electronics Engineering, SRM University, Chennai*

Abstract

Formerly, energy had been inexpensive and management of energy was efficient and was limited to elementary considerations. In the current scenario, due to a rapid increase in demand, complexity of the electrical network, probability of contingency and electricity cost have equally increased. In the recent past, Smart Grids are proven to be the best way to minimize these problems in an easier and smart way. Smart grid is defined as an electric network which has information technology fused to it. This paper proposes a way to reduce the total electricity cost in a smart grid using Genetic Algorithm. The system considered has renewable energy and battery banks apart from the grid to meet the demand. Short term time averaged electricity cost is formulated as an objective for optimization by GA with discharge of battery, energy from the grid to charge battery and meet load etc. as decision variables. The optimization problem is run for a 24 hours data of renewable input, real-time electricity price and load using MATLAB software; and the obtained results are furnished.

Keywords: *Smart grid, optimization of grid, Genetic Algorithm optimization, real time pricing, energy storage.*

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1. INTRODUCTION

Smart grid is a network with optimization techniques which minimizes network losses, voltage levels, increases reliability, and improves management by using real - time measurements. It is a system that uses sensors and has computing control and ability to integrate the users connected to it. The smart grid is about operating transmissions and monitoring to ease the connection and the action of genera-tors. It is beneficial at both the grid side and demand side in terms of energy efficiency. The essential feature of the computerized smart grid is its automation technology, which adjusts and alters a single or millions of equipments from a salient position. Smart grid would also make the integration of the intermittent renewable energy sources and electric vehicles on to the grid easier.

There are two kinds of energy demands in smart grid, namely elastic and inelastic energy demands. This pa-per considers a smart grid with an inelastic demand, renewable sources of energy and energy storing battery banks; and proposes to minimize the short term time averaged cost of electricity by considering the discharge of battery, energy drawn from grid to meet the load, energy drawn from grid to charge batteries and a control variable – which decides the amount of renewable energy to be used – as four decision variables. The multi-variable single-objective optimization is performed using Genetic Algorithm in MATLAB software for a real-time data of electricity-price, renewable energy in-put and the total energy demand of the utilities. Optimal values of the time averaged electricity cost for different battery storage capacities are obtained.

The detailed modeling of the smart grid system considered is given in the next section, followed by the stochastic problem formulation, the detailed optimization algorithm, system data and the results obtained.

2. SYSTEM DESCRIPTION

This paper considers a smart grid system which also includes renewable energy generation by the consumers and a battery bank at the consumers' end for energy storage; apart from the consumers linked to the power grid. The schematic of the system considered [18] is shown in Fig. 1. The renew-able energy generated is stored in the energy storage device i.e., battery bank. The battery operating life will be affected as it gets charged and discharged continuously. To prevent the battery from this damage of overcharging and over-discharging a controller is used. The controller controls the action of battery and regulates the charging and discharging of the battery. An inverter is connected to convert DC to AC before supplying it to the appliances. The detailed description of each component of the system is given in the following sub-sections.

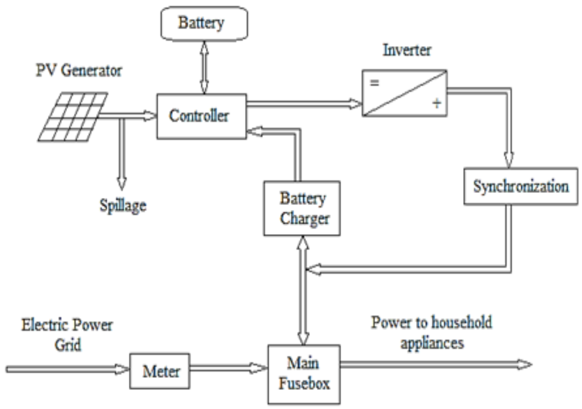

Fig -1: Schematic of the Smart Grid

2.1 Renewable Energy Generation

The renewable energy source considered in this system is solar energy. The detailed modeling of the photovoltaic panels is not dealt with in this paper and hence it is assumed that the output from the renewable source of energy is avail-able for each time slot t (i.e., 1 hour). S(t) is considered to be the amount of renewable energy generated in the time slot t. The amount of renewable energy used is decided by a decision variable, which is described in the next section and the amount of renewable energy generated in a day is also plot-ted in the further sections.

2.2 Battery Bank – Energy Storage

A battery bank is used at the consumer side to store the renewable energy generation; and use the stored energy at any particular time of energy requirement. In general, unused batteries discharge some amount of energy with the passing of time. For simplicity, this aspect of the battery is neglected. The amount of charge present in the battery is described by a term SOC(t), which is the State of Charge of the battery at a time slot t. The SOC level of a battery in this paper is denoted by B(t).

Most of the inelastic load, which is considered in this paper, is met by the battery. The battery is charged by a portion of the renewable energy generated by the consumer and also by the energy bought from the grid – whenever necessary and when the electricity price is low. The latter condition is attempted to be met by making the amount of power drawn from the grid to charge battery [$G_b(t)$] a decision variable in the optimization.

The amount of energy discharged from the battery, in each time slot t, to meet the load is taken as D(t), which is limited by the maximum discharge rate D_{max}. The detailed equations for computing the SOC level for the next time step is given in the next section.

2.3 Energy Demand

This paper considers the demand at the consumer side to be inelastic, i.e., the energy demand arises only at particular instants of time and particular durations; and the energy demand at that particular time has to be met instantaneously. This is attempted to be done primarily by batteries; and when the battery is unable to meet the demand, energy is bought from the grid to directly meet the demand. The amount of energy bought from the grid to meet the demand is given by $G_l(t)$.

The optimization algorithm is executed for a 24 hour demand, which is furnished in the further sections. As the objective of the optimization is to minimize the electricity cost, energy to meet the unmet load is to be bought from the grid only when necessary and mostly when the electricity price is low. Like in the case of battery charging from the grid power, the above mentioned condition is at-tempted to be satisfied by considering $G_l(t)$ as a decision variable for the optimization.

3. PROBLEM FORMULATION

As mentioned earlier, the energy demand in smart grid can broadly be classified into two – elastic and inelastic. The energy demand appliances in household which are elastic are air conditioner, dish washer, heater etc, while some other energy demands of residential households are inelastic, such as lighting, television, computers etc. This paper considers inelastic energy demand, the energy requests of which must be met exactly in the time slot t (i.e., only whenever necessary).The energy demand, battery SOC level, electricity price, and renewable energy generation can be directly monitored by the splitter controller [18]. Another controller is used to determine the portion of renewable energy to be stored into the battery, which also monitors the status of renewable energy generation and battery SOC level.

3.1 Renewable Energy Generation

Assuming that the renewable energy generation, S(t) is first stored in the battery before it can be used in the next time slot; a controller is used to regulate the portion γ(t) of the generated renewable energy to be stored into battery for each slot t in order to prevent battery overflow. The remaining portion of renewable energy generated is spilled. Hence, we limit the control variable γ(t) by

$$0 \leq \gamma \leq 1 \quad (1)$$

Moreover, the amount of renewable energy generation S(t), is limited by a maximum value S_{max}. This is mathematically expressed as,

$$0 \leq S(t) \leq S_{max} \quad (2)$$

In order to utilize the time diversity of electricity price, it is assumed that in each time slot t, the amount of energy that can be drawn from the power grid to recharge the battery bank is $G_b(t)$. The state of charge (SOC) level B(t) in the battery evolves according to the following equation:

$$B(t+1) = B(t) - D(t) + \gamma(t)\, S(t) + G_b(t) \tag{3}$$

Where, D(t) is the amount of energy that is discharged from battery to supply demand in slot t. The SOC level in each time step is limited by the following constraint.

$$D(t) \le B(t) \le B_{max} \tag{4}$$

Where, B_{max} is the battery's maximum capacity. The amount of energy discharged from battery is further limited by its maximum discharge level D_{max}, i.e.,

$$0 \le D(t) \le D_{max} \tag{5}$$

The energy amount that can be drawn from the electric power grid to recharge battery for one time slot is also bounded $G_{b,max}$ i.e.,

$$0 \le G_b(t) \le G_{b,max} \tag{6}$$

The time-varying electricity price, C(t), is sent to the consumer's smart meter by the utility company at the beginning of each time slot t. The cost of using renewable energy generated by the consumer itself is taken as zero. $G_l(t)$ is considered to be the power drawn from the electric power grid to directly supply the energy demand in slot t. Since the total electricity drawn from the electric power grid is the sum of the energies drawn to charge battery and meet the demand, the electricity cost for each time slot t is given by $[G_b(t)+G_l(t)]C(t)$.

3.2 Control Objective

Aiming at minimizing the total electricity cost for the customers, the short-term time averaged electricity cost [18], as described in equation (7), is considered as the optimization objective to be minimized.

$$P = \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathrm{E}\left\{C(t)\ \left[G_l(t)+G_b(t)\right]\right\} \tag{7}$$

The inelastic energy demand [18] generated in time slot t is given by the following equation

$$A_{ine}(t) = G_l(t) + D(t) \tag{8}$$

The problem can thus be formulated as the following stochastic optimization objective

$$\min_{D(t),G_b(t),G_l(t),\gamma(t)} P = \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \left\{C(t)\left[G_l(t)+G_b(t)\right]\right\} \tag{9}$$

Subject to the following constraints

$$B(t+1) = B(t) - D(t) + \gamma(t)S(t) + G_b(t)$$

$$D(t) \le B(t) \le B_{max}(t)$$

$$G_l(t) + D(t) = A_{ine}(t)$$

$$0 \le D(t) \le D_{max}$$

$$0 \le G_l(t) \le G_{l,max}$$

$$0 \le G_b(t) \le G_{b,max}$$

$$0 \le \gamma(t) \le 1$$

$$X_{ine}(t) = B(t) - V_{ine} * C_{max} - D_{max} \tag{10}$$

Where, V_{ine} is a control parameter and $X_{ine}(t)$ is the shifted version of battery SOC level B(t) which is used to ensure that the constraint on the SOC level of battery is satisfied. The shifted version of battery SOC level for the next time step is computed by the following equation

$$X_{ine}(t+1) = X_{ine}(t) - D_{max} + \gamma(t) * S(t) + G_b(t) \tag{11}$$

The decision variables considered for the optimization are: D(t) – the amount of energy discharged from the battery; $G_l(t)$ – the power drawn from the grid to directly supply the load; $G_b(t)$ – the power drawn from grid to charge the battery; and $\gamma(t)$ – the control parameter which decides the amount of renewable energy to be stored in battery. The optimization is performed using Genetic Algorithm (GA).

4. OPTIMIZATION ALGORITHM

There are two distinct types of optimization algorithms widely used today, namely – deterministic and stochastic algorithms. Deterministic algorithms use specific rules for moving from one solution to other; while stochastic algorithms use probabilistic translation rules. Genetic Algorithm (GA) is a direct, parallel, stochastic method for global search and optimization, which is used extensively for varied applications. GA is a part of the group of Evolutionary Algorithms (EA), which use the three main principles of the natural evolution: natural selection, reproduction and diversity of the species.

This paper proposes the minimization of the time averaged electricity cost with the decision variables as mentioned in the previous section. The detailed algorithm of the multi-variable single objective Genetic Algorithm is described below.

1. **Initialization:**
   A random initial population (size N) of individuals, x, is created within the bounds of each variable.

2. **Evaluation:**
   Once the population is initialized or an offspring population is created, the fitness function (objective) is computed.

3. **Selection:**
   Selection allocates more copies of those solutions with higher fitness values and thus imposes the survival-of-the-fittest mechanism on the candidate solutions. Many selection procedures namely roulette-wheel selection, stochastic universal selection, ranking selection and tournament selection

   This paper uses Rank + Roulette wheel selection. The individuals are sorted based on their fitness values and are assigned a rank accordingly. The selection probability for each individual is calculated according the following non-linear function:

$$P = \beta(1-\beta)(\text{rank}-1) \qquad (12)$$

   There β is a user defined coefficient. The traditional roulette wheel selection is now used to select the best fit individuals.

4. **Recombination:**
   Recombination, also called crossover, combines parts of two or more parental solutions to create new, possibly better solutions (i.e. offspring).
   This paper uses Blend crossover (BLX) – α crossover operator. Considering two parents from the selection process, the offspring obtained after the crossover is given by

$$x_i^{(1,t+1)} = \left(1-\gamma_i\right)x_i^{(1,t)} + \gamma_i x_i^{(2,t)} \qquad (13)$$

   Where, $\gamma_i = (1+2\alpha)u_i - \alpha$,in which u_i is a random number between 0 and 1.

5. **Mutation:**
   While recombination operates on two or more parental chromosomes, mutation locally but randomly modifies a solution.

   This paper uses non-uniform mutation, according to which the mutated offspring is given by

$$y_i^{(1,t+1)} = x_i^{(1,t+1)} + \tau\left(x_i^{(U)} - x_i^{(L)}\right)\left(1 - r_i^{(1-t/t_{\max})^b}\right) \quad (14)$$

   where τ takes a boolean value -1 or 1, each with a probability of 0.5, t_{max} is the maximum number of allowed generations, and b = 0.5 is a user defined parameter.

6. **Combined Population:**
   To preserve elitism, both parent and offspring population is combined and then sorted based on their fitness values. The first N individuals are chosen for the next generation.

7. **Iterate:**
   Repeat steps 2–6 until termination condition is met (i.e., until fitness value converges).

5. INPUT DATA

The electricity price data used in this paper is collected from the California Independent System Operator CAISO consisting of an hourly average price C(t) for 24 hours[19] and is illustrated in Fig. 3.The average renewable energy data used is taken from the Measurement and Instrumentation Data Center (MIDC) at National Renewable Energy Laboratory [20] and is shown in Fig- 4.

Depending upon the energy consumed by appliances during each time slot t, the inelastic load for 24 hours [21] is shown in Fig- 2.

Considering the parameters D_{max}= 30KW, $G_{l,max}$ = 30 KW and $G_{b,max}$ = 20 KW [18], optimization using GA is performed and the results are furnished in the next section.

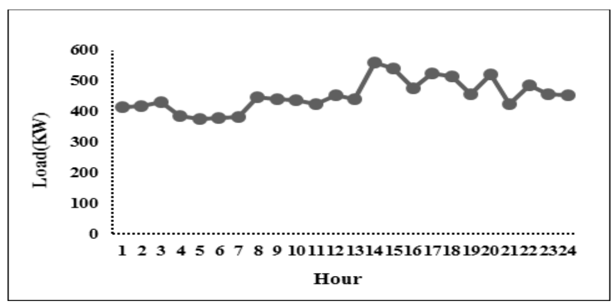

Fig- 2: Average hourly load for 24 hours

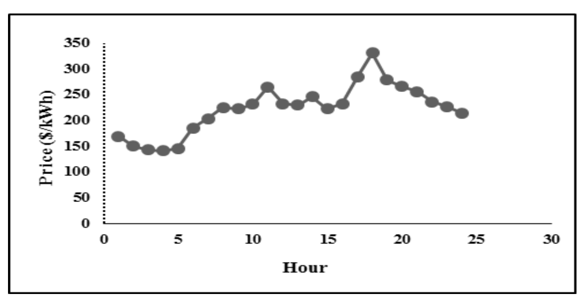

Fig- 3: Average hourly market price for 24 hours

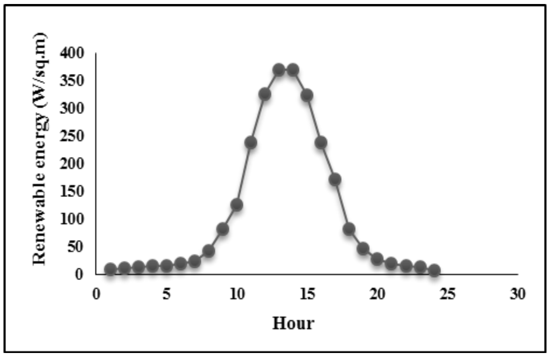

Fig-4: Average hourly renewable energy for 24 hours

6. PERFORMANCE EVALUATION

In this paper multi-variable, single objective Genetic Algorithm is proposed and simulated for the 24 hours data of renewable energy, electricity price and inelastic energy demand mentioned in the previous section. The algorithm is simulated using MATLAB to optimize the short-term time averaged electricity cost for different values of B_{max}. The best fitness values for B_{max}={100,150,200}KW-slot is tabulated in Table 1 and is illustrated in Fig- 5.

It can be observed from the results, that the total electricity cost is highest when Bmax=100 and is lowest when Bmax=200. It can thus be seen that the total electricity cost for consumers is reduced by increasing the capacity of the battery banks.

Table -1: Fitness values for different B_{max} value for inelastic energy demand

Iterations	Time Averaged Electricity Cost		
	B_{max}=100 KW	B_{max}=150 KW	B_{max}=200 KW
1	0.640871	0.298791	0.753732
2	0.317684	0.298791	0.753732
3	0.185219	0.298791	0.753732
4	0.185219	0.298791	0.753732
5	0.185219	0.298791	0.753732
6	0.185219	0.298791	0.753732
7	0.152103	0.298791	0.753732
8	0.152103	0.298791	0.621267
9	0.152103	0.232559	0.538477
10	0.152103	0.232559	0.488802
11	0.152103	0.21807	0.141082
12	0.152103	0.166326	0.091407
13	0.152103	0.166326	0.091407
14	0.152103	0.166326	0.091407
15	0.152103	0.166326	0.091407
16	0.152103	0.13321	0.091407
17	0.152103	0.13321	0.091407
18	0.152103	0.13321	0.091407
19	0.152103	0.100094	0.025175
20	0.152103	0.100094	0.025175
21	0.151068	0.100094	0.025175
22	0.151068	0.100094	0.025175
23	0.150033	0.100094	0.008972
24	0.149702	0.098631	0.008972
25	0.149702	0.095954	0.008972
26	0.148998	0.095954	0.008617
27	0.148998	0.095954	0.008617
28	0.148998	0.093998	0.000338
29	0.148998	0.093998	0.000338
30	0.148998	0.093884	0.000338
31	0.147963	0.093884	0.000338
32	0.147963	0.093338	0.000338
33	0.147963	0.091928	0.000338
34	0.147963	0.091815	0.000338
35	0.146929	0.075791	0.000338
36	0.146929	0.075256	0.000338
37	0.146929	0.025582	0.000338
38	0.146929	0.025582	0.000338
39	0.146535	0.025582	0.000338
40	0.145894	0.025582	0.000338
41	0.145894	0.025582	0.000338
42	0.145894	0.025582	0.000338
43	0.145303	0.012678	0.000338
44	0.145303	0.012678	0.000338

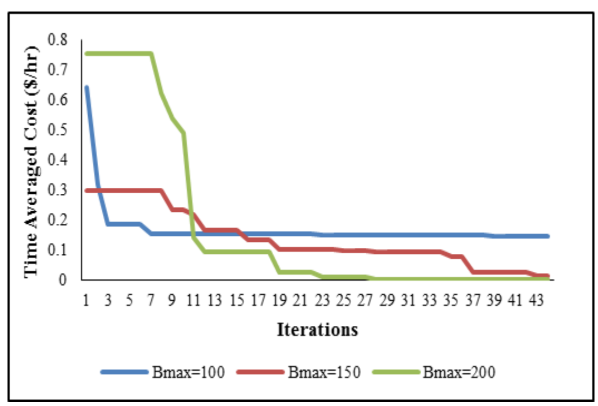

Fig- 5: Comparison of total cost for different Bmax values with inelastic energy demand.

7. CONCLUSIONS

In this paper, the optimization of total electricity cost for the consumers with inelastic load in a smart grid is achieved by minimizing the short-term time averaged electricity cost. The inelastic load being time specific is supplied mostly by batteries; which is charged by the renewable energy generation and the grid. The optimization aims at charging the battery when electricity price is less and discharging the battery when electricity price is high. Optimization is performed by multi-variable, single objective Genetic Algorithm for a 24 hour data of real-time electricity price, renewable energy generation and total inelastic energy demand of the utilities. An optimized minimum cost is obtained for three cases of different battery capacities, and it is observed that the total electricity cost is lower for higher battery capacity and vice versa.

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BIOGRAPHIES

Gundi. Anny Mary received B. Tech degree in Electrical and Electronics Engineering from Jawaharlal Nehru Technological University Kakinada Andhra Pradesh, India, in May 2012 is pursuing M. Tech degree in Power Systems from SRM University, Tamilnadu, India, 2012-14. Her research interests includes stochastic network optimization and smart grids.

R. Rajarajeswari received her B.E and M.E degrees in Electrical and Electronics Engineering from Manonmaniam Sundaranar University of Technology, Tamilnadu and Anna University of Tamilnadu, India, in July 2001 and April 2006, respectively. She has published 1 international and 4 national papers in reputed journals and conferences.