Optimization of Solar-PV Model for LED Lighting by Simulated Annealing With Improved Reliability and Less Capital Cost

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Abstract: **This paper presents the optimization of design of solar PV module to fed LED driver. In the varying weather conditions, the reliability and cost of solar module can be optimized by its optimal design by simulated annealing method.This paper recommends an optimal sizing method to optimize the configurations of solar–PV system employing battery banks.The decision variables included in the optimization process are the PV module number, battery number, PV module slope angle. The proposed method has been applied to the analysis of a LED lighting system.**

Keyword: Solar PV module, LED system, simulated annealing,optimization

I. INTRODUCTION

The energy demand is rising at rate higher than the energy is being generated. The non-conventional energy sources are best alternatives for power generation. The solar energy is one of the potential energy sources which available easily and abundantly almost everywhere. The uncertain weather conditions affect the output power of solar PV modules over a period of year. There is need of optimization of configuration of solar PV module considering power supply reliability and annual capital cost.

There are various other methods of optimization like neural network, genetic algorithm, random search methods, gradient method and iterative search methods.

Neural networks: The main difference compared with neural networks is that neural networks learn how to approximate a function, while simulated annealing searchesfor a global optimum. Neural networks are flexible function approximators while SA is an intelligent random search method. The neural networks have the benefit of adaptive characteristics in modeling changing environments. However, the more power requirement of SA limits its use as a real-time application.

Genetic algorithms:It providesmerging to an optimal point. Nevertheless, it should be expected that GA may be better suited for some problems than SA.

Random Search: It uses brute force approach for difficult functions which is a random, or an enumerated search. The search space is selected randomly, or in some systematic way, and their fitness evaluated. This is anunintelligent strategy, and is rarely used by itself.

Gradient methods:

There are number of methods for optimizing continuous functions which rely on using information about the gradient of the function to guide the direction of search. If thederivative of the function cannot be computed, because it is discontinuous, these methodsoften fail. Such methods are generally referred to as hill climbing. They can perform well on functionswith only one peak (unimodalfunctions). But on functions with many peaks, (multimodal functions), theysuffer from the problem that the first peak found will be climbed, and this may not be the highest peak.

Having reached the top of a local maximum, no further progress can be made.

Iterated Search:By combining random search and gradient search to give an iterated hill climbingsearch. Once onepeak has been found, the hill climb is restartedbut with another randomly chosen starting point.This technique is simple and can perform well if the functions haveonly fewlocal maxima. However, since each random trial is carried out in isolation, no overall picture of theshape of the domain is obtained. As the random search progresses, it continues to allocate its trialsevenly over the search space. This means that it will still evaluate just as many points in regions found tobe of low fitness as in regions found to be of high fitness.Both SA and GAs, by comparison, start with an initial random population, and allocate increasing trialsto regions of the search space found to have high fitness. This is a disadvantage if the maximum is in asmall region, surrounded on all sides by regions of low fitness. This kind of function is difficult to optimize by any method, and here the simplicity of the iterated search usually wins.

In [1] four simulated annealing based multiobjective algorithms to solve multiobjective optimization of constrained problems with varying degree of complexity along with a new algorithm. In [2] the history and overview of simulated annealing is explained. In [3] basic terminology and principle of simulated annealing is illustrated. The effectiveness of a hybrid of simulated annealing (SA) and the simplex algorithm for optimization of a chromatographic separation has been examined in [4]. [5] Proposes a method for modeling and simulation of photovoltaic arrays. The method is used to obtain the parameters of the array model using its datasheet information. [6] Presents a Simulated Annealing based technique to address the assembly line balancing problem for multiple objective problems when paralleling of workstations is permitted. [7] review the central constructs in combinatorial optimization and in statistical mechanics and then develop the similarities between the two fields.

II. OVERVIEW OF SIMULATED ANNEALING

Simulated annealing is a computational stochastic techniquefor obtaining near global optimum solutions to combinatorial and function optimization problems. The methodis inspired from the thermodynamic process of cooling(annealing) of molten metals to attain the lowest free energystate Kirkpatrick et al. When molten metal iscooled slowly enough it tends to solidify in a structure ofminimum energy. This annealing process is mimicked by asearch strategy. The key principle of the method is to allowoccasional worsening moves so that these can eventuallyhelp locate the neighborhood to the true (global)minimum.

III. SIZING THE PV PANEL AND BATTERY

In order to appropriate PV array sizing, sun hour, load data, days of autonomy, and solar radiation should be considered.

A.Sun Hour: The equivalent number of sun hours of standard full solar irradiance at 1000W/m2 should be obtained by using the solar radiation data on the array plane to estimate the daily module output. Average available AH/day production from the PV array can be calculated by multiplying the number of sun hours by the rated value of the module peak current.

B.Load Calculation: Proper determination of the load isone of the most important factors in sizing a stand-alone PV system. By multiplying each load current to its daily duration and summing the results, it is possible to calculate equivalent daily load consumption. The AH of the load can be calculated by multiplying the duration to the momentary current if the duration of the momentary load is known. If the duration of the momentary load is not known, the time is assumed to be 1 min and the load consumption is calculated accordingly. For more sensitive and accurate calculation of the load data, the momentary current, running current, parasitic current, and load coincide, and the maximum and minimum load voltages should be considered.

C.Days of Autonomy: Autonomy is the length of time that the battery of a PV system can supply load demands without receiving energy from the PV array. Therefore, the battery should be sized to support the load during periods of low or non-solar radiation since the array is sized to replace the AH capacity of the battery used by the load and system losses. Battery capacity directly determines system availability. The larger battery provides a greater number of autonomy days.

D.Solar Radiation: The solar radiation for the month with the worst-case solar radiation at a certain tilt angle should be used if the average load is constant for all months. This value is equivalent to sun hours, which is generally presented in kilowatt-hour (kWh)/m2. This value is used to determine the size of the PV array.

E.PV Array Sizing: Solar radiation, array-to-load ratio, load calculation, and system losses should be taken into account for the sizing of the PV array. These factors are explained as follows:

i. PV Module Selection: Some PV modules may have advantages or drawbacks when compared to others, depending on performance under various irradiance conditions and PV array size. Single and polycrystalline silicon and amorphous silicon are the most common PV modules.

ii. System Losses: System losses should be included in the sizing calculations, since they affect the proper sizing of the PV array. Wire and connection losses, parasitic losses (such as controller or sun tracker power requirements), battery charge–discharge efficiency, dust on the array, and inverter and line losses should be considered in the evaluation of system losses as a percentage of the system load. Usually, these losses are about 10–20% of the rated system load. Theperformance of the system may reduce if the losses are not estimated accurately.

iii. Determination of the Number of Series and Parallel connected PV Modules are calculated as:

Number of modules in series:

$$Ns = \frac{Vsystem}{Vmodule}$$

Where, Ns is the number of series-connected PV modules, Vsystem is the rated system voltage, and Vmodule is the nominal voltage per module.

The number of module strings in parallel can be calculated as;

$$Np = \frac{L_{DA} \text{ x } (A{:}L)}{((1-SL) \text{ x } SH \text{ x } I_{mp})}$$

Where NP is the number of parallel strings, LDA is the average daily load, A:L is array to load ratio, SH represents sun hours, SL represents system losses, and Imp is the module current at maximum power.

The maximum power output of the PV system can be calculated by,

$$P_{PV} = N_p.N_s.P_{Module}.\eta_{MPPT}.\eta_{oth}$$

Where, P_{Module} is the maximum power output delivered by the PV module. $\eta_{MPPT}$is efficiency of the maximum power point tracking, η_{oth} is the factor representing the other losses such as the loss caused by cable resistance, accumulative dust, etc.

IV. POWER SYSTEM RELIABILITY MODEL

The power system model depend upon probability of power failure (PPF). PPF is defined as the probability thatan insufficient power supply results when the solar PV system

(PV array and battery storage) is unable tosatisfy the load demand. It is a feasiblemeasure of the system performance for an assumed orknown load distribution. A PPF of 0 means the load will always be satisfied; and PPF of 1 means that the loadwill never be satisfied.

PPF can expressed as

$$PPF = \frac{\sum_{t=0}^{T} \text{Power failure time}}{T}$$

$$PPF = \frac{\sum_{t=0}^{T} \text{Time}\left(P_{available}(t) < P_{needed}(t)\right)}{T}$$

Where T is the number of hours in this study with hourly weather data input. The power failure time is defined as the time that the load is not satisfied when the power generated by the PV array is insufficientand the storage is depleted. The power needed by the load side can be expressed as

$$P_{needed}(t) = \frac{P_{ACload}(t)}{\eta_{inverter}(t)} + P_{DCload}(t)$$

and the power available from the solar-PV system isexpressed by

$$P_{available}(t) = P_{PV} + C.V_{bat}.\text{Min}\left[I_{bat\,max} = \frac{0.2C'_{bat}}{\Delta t}, \frac{C'_{bat}(SOC(t) - SOC\,min)}{\Delta t}\right]$$

where C is a constant, 0 for battery charging process and 1 for battery discharging process. Cbat is the available or practical capacity of the battery,SOC(t) is the battery state of charge at time t, and it is calculated based on the battery SOC at the previous time t-1.

Using the above developed objective function according to the PPF technique, for a given PPF value for one year, a set of system configurations, which satisfy the system power reliability requirements, can be obtained.

V. ECONOMIC MODEL BASED ON ACS CONCEPT

The economical approach, according to theconcept of annualized cost of system (ACS), is developedto be the best benchmark of system cost analysis in thisstudy. According to the studied solar system,the annualized cost of system is composed of the annualizedcapital cost Cacap, the annualized replacement costCarep and the annualized maintenance cost Camain. Three main parts are considered: PV array, battery and the other devices. Then, the ACS can be expressed by

ACS = Cacap(PV + Bat +Others)+Carep(Bat)
+ Camain(PV+ Bat + Others)

VI.METHODOLOGY OF THE OPTIMIZATION MODEL

The following optimization model is a simulation tool toobtain the optimum size or optimal configuration of asolar–PV system employing a battery bank interms of the PPF technique and the ACS concept by usinga genetic algorithm. The flow chart of the optimizationprocess is illustrated in Fig.

The decision variables included in the optimization processare the PV module number NPV,battery number Nbat, PV module slope angle β’. A year of hourly data including the solar radiation on the horizontal surface, ambient air temperature and load power consumption is used in the model.The initial assumption of system configuration will besubject to the following inequalities constraints:

$$\text{Min}(NPV, Nbat) \geq 0$$

$$0° \leq \beta' \leq 90°$$

VII. SA ALGORITHMS IMPLEMENTATION OF OPTIMIZATION OF SOLAR-PV MODULE

Objective function: 1.Minimize PPF

2. Minimize ACS

Step1.Initialization of the values temperature, T, parameter α and iterations number criterion. Find, randomly, an initial feasible solution, which is assigned as the current solution Si and evaluate PPF and ACS with all constraints satisfied.

Step 2. Set the iteration counter to $\mu=1$

Step 3. Find a neighboring solution Sj through a random perturbation of the counter one and calculate the PPFand ACS.

Step 4. If the new solution is better, we accept it, if it is worse, we calculate the deviation of cost $\Delta S=Sj-Si$ and generate a random number uniformly distributed over $\Omega\epsilon$ (0, 1).

If

$$e^{\frac{\Delta s}{t}} \geq \Omega \in (0,1)$$

accept the new solution Sj to replace Si.

Step 5. If the stopping criterion is not satisfied, reduce temperature using parameter α as

$$T(t) = \alpha.t$$

And go to Step 2.

VIII. CASE STUDY

The LED street lighting load of 1Kw, operating for 12hours from 7PM-7AM located in Nasik(longitude-20N,latitude-73E) with average solar radiation of 5.03Kwh/m2(0.6-6.7Kwh/m2)and temperature varying from 17°C to 40°C(i.e. 290°K to 313°K).

Specifications and cost of PV module:

Voc = 21v,Isc = 6.5A, Vmax = 17V,

Imax = 5.73A, Pmax=100W,life= 25years,

capital cost = 6500 USD/KW, Maintenance cost 10% of capital cost.

Specifications and cost of battery:

Ah=1000,V=2V/cell, efficiency=90%,life=8yrs,capital cost = 1500USD/KAh,maintenance cost=50USD/KAh.

The optimization by simulated annealing results in following solution:

For probability of power failure(PPF) of 1%,

Size PV array = 4.855KW and 18 number of batteries for initial cost = 58,558USD, cost of energy is 1.54 USD/Kwh.

The above results are then modified for system voltage requirement of 230V. Number of PV modules = 5x1000/100 = 50Nos.

Number of modules in series,

Ns = 230/17= 13.53 ≈ 14.

Therefore number of modules in parallel,

Np= 50/14=3.57≈4.

Therefore size of PV arrays comes to be

= 14*4=56 module of 5.6KW.

Therefore for this PV configuration, the number batteries required are reduced to 13 from 18. Then the initial cost of system rise to 55,900USD and cost of energy be 1.56USD/Kwh. Simulation results are given below:

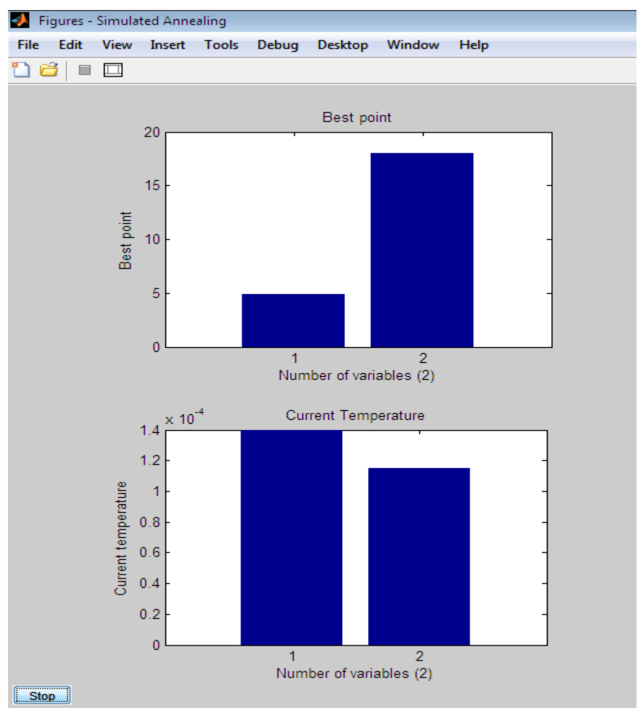

Figure1.Optimized Variable and Temperature plot

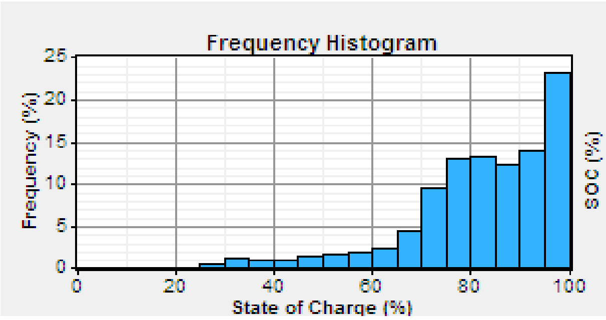

Figure.2.Frequency Vs SOC plot

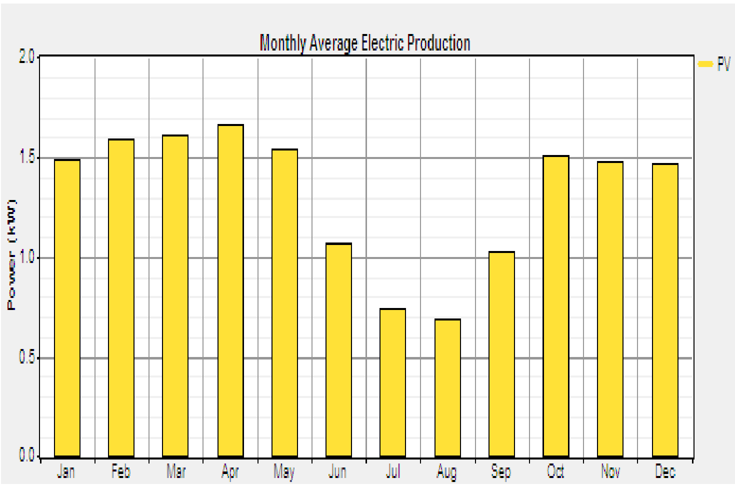

Figure.3.Monthly Average Electric Production

IX. CONCLUSION

In this paper, the development of a method for themathematical modeling of photovoltaic arrays and battery is analyzed. The system is simulated in MATLAB.As with genetic algorithms a major advantage of SA is its flexibility and robustness as a global searchmethod. A disadvantage is that the SA methods are computation-intensive. There exist faster variants of basicsimulated annealing, but these apparently are not as quite easily coded and so they are not widely used. The proposed model can be used for various types of loads. The result may vary with varying weather condition.

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