Optimal Sizing of Renewable Hybrid Energy System: A Review of Methodologies

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ABSTRACT

The ever-growing energy demand, the intermittent nature of renewable energy resources such as wind, photovoltaic etc coupled with issues of reliability makes the hybrid renewable energy systems more preferred. Hybrid energy sources offers better reliability and cost effectiveness than a single energy source. One of the most important issues related to hybrid renewable energy systems is obtaining the optimal size of their parts so as to utilize them efficiently and economically. Determining the optimal size of hybrid energy systems helps to avoid over-sizing or under-sizing of the system which will subsequently affect the cost and reliability of the system. Optimal sizing becomes complex when considering multiple hybrid mix while at the same time considering various objectives such as cost, CO_2 gas emission and reliability. This paper aims at critically reviewing the various **optimization techniques** used in optimal sizing of various combination of hybrid energy sources for effective selection of the appropriate sizing method for hybrid renewable energy systems. It has been found that meta-heuristic techniques are well suited for optimal sizing of the hybrid energy systems with Genetic Algorithm and Particle Swarm Optimization techniques being the most commonly used Algorithms.

INTRODUCTION

Nigeria has been experiencing electricity shortage for the past two decades. The utility grid is characterized by high unreliability index with power. At any given period when the grid power is available, the supply voltage fluctuates. This consequently gives rise to load shedding, which has adverse effects on domestic, commercial and industrial activities. This has resulted in the use of fossil-powered sources. However, the socio-economic and environmental implications associated with the use of fossil fuelled generators are very alarming. This has triggered the rapid increase in greenhouse gas emissions to the atmosphere and a consequential rise in fuel price. The greenhouse effect has the potential of creating dangerous climatic changes with devastating effects on the ecosystem. An incentive of renewable energy is that they are eco-friendly with little to zero greenhouse gas and CO_2 emissions.

A promising solution to these problems is the application of the stand-alone Hybrid Energy System (HES), which combines renewable/conventional sources with battery. Successful implementation of this technology depends largely on its optimal design. An important aspect of this design is sizing which involves calculating the size of the different components required to supply the loads during the worst climatic conditions at minimum cost. A major problem with the use of renewable energy such as solar, wind etc, is that they are stochastic and intermittent in nature because the usage of an individual renewable source of energy cannot guarantee continuous supply of power.

One major way to effectively utilize renewable energy sources considering their intermittency is through hybridization which implies the combination of two or more renewable/non-renewable energy sources. Therefore, the determination of the optimal size of a hybrid energy system creates an optimization problem that increases in complexity as the number of energy sources and constraints increases.

OPTIMIZATION

Optimization is the act of obtaining the best result under given circumstances. In design, construction and maintenance of any engineering system, engineers have to take many technological and managerial decisions at several stages. The ultimate goal of all such decisions is either to minimize the effort required or to maximize the desired benefit. Since the effort required or the benefit desired in any practical situation can be expressed as a function of certain decision variables, optimization can be defined as the process of finding the conditions that give the maximum or minimum value of a function.

Optimal Sizing Methodologies

Linear Programming or Linear Optimization

Linear optimization may be defined as the problem of maximizing or minimizing a linear function that is subjected to linear constraints. Linear programming can also be defined as a method of considering different inequalities relevant to a situation and calculating the best value that is required to be obtained in those conditions. It is a mathematical method which deals with minimization or maximization of linear functions subject to linear constraints. The constraints may be equalities or inequalities. Linear programming problems are an important class of optimization problems that helps to find the feasible region and optimize the solution in order to have the highest or the lowest value of the function. In other words, linear programming is considered as an optimization method to maximize or minimize the objective function of the given mathematical model with the set of some requirements which are represented in the linear relationship. The main aim of the linear programming problem is to find the optimal solution. The linear programming problems can be used to get the optimal solution for the following scenarios, such as manufacturing problems, transportation problems, and allocation problems. The linear programming problem can be solved using different methods such as the graphical methods, simplex method. The simplex method is one of the most popular methods used in solving linear programming problems. It is an iterative process to get the feasible optimal solution. In this method, the value of the basic variable keeps transforming to obtain the maximum value for the objective function. When the decision variables of a linear program are restricted to be integers, it is said to be a pure integer programming problem. When not all decision variables are restricted to be integers, then it is referred to as a mixed integer linear program. In its simplest terms, a linear programming problem is solved by graphing the constraints to come up with a region known as the feasibility region within which acceptable solutions can be found. The optimization equation developed for the problem is then used to test for the most optimal point within the feasibility region. A summary of works employing variants of the linear programming method to solve for the optimal sizing of components of a hybrid renewable energy system is presented below. **Chen and Gooi** (2010). proposed a new method for optimal sizing of an energy storage system (ESS). The ESS was to be used for the storage of energy at times of surplus and for re-dispatch later when needed. They considered the Unit commitment problem with spinning reserve for micro-grids. Their total cost function took account of the cost of the Energy Storage System (ESS), the cost of output power and the cost of spinning reserve. They formulated the main method as a mixed nonlinear integer problem (MNIP) which was solved in a mathematical programming language (AMPL). Effectiveness of the proposed method was then validated by a case study where optimal ESS rating for micro-grid was determined. Results indicated that a properly sized ESS not only stored and re-dispatched renewable energy appropriately but also reduced the total cost of the micro-grid. **Bahramirad and Reder** (2012). proposed that Energy Storage systems are fast response devices that add flexibility to the control of micro-grids and provide security and economic benefits to the micro-grid. Thus, they have a major role in the long term and short-term operation of micro-grids. In their work, they evaluated the benefits of ESS in in islanded operation of micro-grids. Long term unit commitment was then used to obtain the optimal unit scheduling. A practical model for an Energy Storage System was used and probabilistic reliability calculation method used to find expected energy not served and accordingly calculate cost of reliability of the micro-grid. They solved the optimization problem using mixed integer programming method. **Chen et al**. (2012). presented a cost benefit analysis-based method for optimal sizing of an energy storage system in a micro-grid. They considered the unit commitment problem with spinning reserve for micro grids. Wind speed was modeled using a time series whereas solar irradiances is modeled via feed forward neural network techniques with forecasting errors being accounted for. They also presented two mathematical models for islanded and grid operation. The main problem was formulated as a mixed linear integer problem (MLIP) which is solved in AMPL. Effectiveness of the proposed method was then validated via a case study. Quantitative results indicated that optimal size for a BESS existed but differed for both grid connected and islanded mode of operation.

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Genetic Algorithm

Genetic algorithm (GA) is a method for solving both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution. It is an optimization method based on the genetic process of biological organisms. By mimicking this process, GA has the capability to provide solutions to complex real world problems.GA approaches are global search heuristics, which are subsets of evolutionary algorithms. They are elitist search techniques with a simulation in which the greatest individual in a generation is passed on to the next generation without degeneration. It employs Darwin's theory to describe the survival of species in a population, which consists of three fundamental processes (selection, crossover and mutation) and three critical regulatory parameters (population size, crossover and mutation rates). Following a random selection of people from the initial population ('the parents'), the three major processes are used to create the 'children' for the following generation. After that, the technique continues with consecutive generations of individual solution adjustments until the required optimal population is achieved. By utilizing broad crossover and mutation procedures that produce new populations at every stage of the process, GA avoids jeopardizing adherence to the local optimum. However, to solve the optimization problem, GA requires a large number of control decision variables as input. It is important to figure out what the best controlling coefficients are because changing them can change the algorithm performance. The input data of GA based methodology can be meteorological conditions and the unit prices of the projected hybrid system components including installation and maintenance costs. Genetic algorithms are a type of optimization algorithm inspired by the process of natural selection and genetics. They are particularly useful for solving optimization problems where traditional optimization techniques may be less effective or infeasible due to the complexity of the search space. The general flow chart of a simple Genetic Algorithm is shown below.

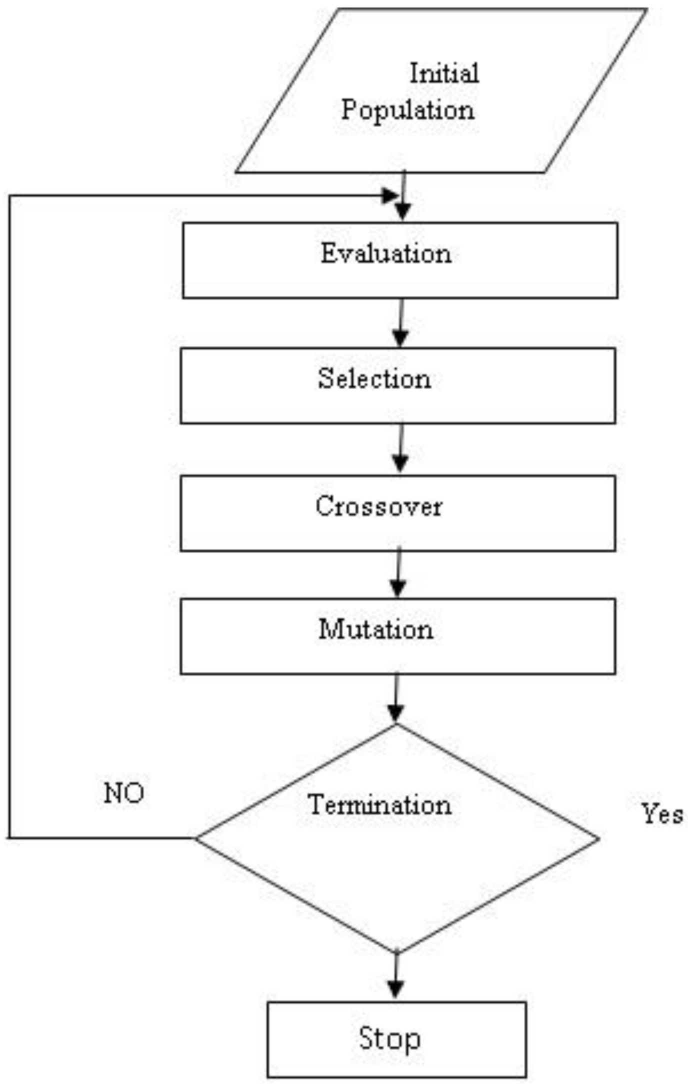

Figure 1 Flow Chart of a simple Genetic Algorithm

1. **Initialization:** The algorithm starts by creating a population of potential solutions to the optimization problem. Each solution is typically represented as a chromosome, which is a string of values (genes) that encode a potential solution.

2. **Evaluation:** Each chromosome in the population is evaluated using a fitness function that quantifies how good the solution encoded by the chromosome is with respect to the optimization problem. This fitness function guides the search towards better solutions.

3. **Selection:** Individuals in the population are selected for reproduction based on their fitness. Individuals with higher fitness values are more likely to be selected for reproduction, mimicking the principle of 'survival of the fittest'

4. **Crossover:** During the crossover (recombination) phase, pairs of selected individuals (parents) exchange genetic information to create new offspring (children). This process helps in introducing diversity into the population and potentially produce better solutions by combining good characteristics from different individuals.

5. **Mutation:** In the mutation phase, some random changes are introduced into the offspring's chromosomes to maintain genetic diversity in the population. Mutation helps in preventing the algorithm from getting stuck in local optima and explores new regions of the search space.

6. **Replacement:** The new offspring (children) replace some individuals in the current population. The selection of individuals for replacement can be based on various strategies, such as elitism (keeping the best individuals) or generational replacement.

7. **Termination:** The algorithm continues to iterate through the selection, crossover, mutation and replacement steps for a certain number of generations or until a termination criterion is met (e.g a satisfactory solution is found or a maximum number of iterations is reached). By iteratively applying these steps, genetic algorithms explore the search space and evolve a population of solutions towards better solutions over successive generations. Through the principles of selection, crossover and mutation, genetic algorithms can efficiently search for optimal or near-optimal solutions to a wide range of optimization problems.

Some constraints can also be added to the algorithm, constraints can be given as limiting the maximum number of PV panels on a building roof that is constrained by roof area, limiting the number of wind turbines installed on specific land constrained by land area or limiting the power change slope of a fuel cell etc. A fitness function must be defined as an input to the GA approach, Moreover, the parameters for GA operators such as the percentage of selection and rate of mutation should be provided before the GA-based sizing process. With the given input data, GA-based sizing methodology provides an iterative procedure utilizing the GA operators until a predefined termination criteria or maximum iteration numbers are reached. A GA consists of five components. These are an initial random population generator, a fitness evaluation unit and genetic operators for 'selection', 'crossover' and 'mutation' operations. With the random population at the start, GA algorithm offers random sizes for the hybrid system components that satisfy the load demand and power generation balance at each step. Each of the random solution is evaluated according to the defined fitness function. 'Selection' operator selects the predefined percentage of the initial population due to their fitness value. Utilizing these selected solutions, 'crossover' operator provides new possible solutions with the aim of achieving higher fitness values. For example, for a PV-wind-fuel cell hybrid system, the selection operator may choose two different solutions of 15/25/20 (15kW wind turbine, 25kW PV system, 20kW fuel cell) and 10/30/17 (10kW wind turbine, 30kW PV system, 17kWfuel cell). With an example crossover operation, two new possible solutions that can either have a lower or greater fitness value than the current solution can be provided as 10/30/20 (10kW wind turbine, 30kW PV system,20kW fuel cell) and 15/25/17 (15kW wind turbine, 25kW PV system, 17kW fuel cell). The new population is created with the solutions selected by the 'selection' operator and the new solutions created by the 'crossover' operator. Then the selection of the solutions with greater fitness values and creation of a new population continues at each iteration during the iteration procedure. During the iteration process, a 'mutation' operator can also be applied to prevent getting stuck at a local minimum. As an example, changing the fuel cell size from 20kW to 10kW in a 15/25/20 solution (15kW wind turbine, 25kW PV system, 20kW fuel cell) can be provided by mutation operator. This procedure consisting of the selection, crossover and mutation cycle continues until the termination of the iterative process. The most significant advantage of GA for use in hybrid system sizing is that it can easily jump out of a local minimum and has quite efficient capability to find the global optimum. Besides, the advantage of being able to code infinite number of parameters on a chromosome makes it suitable for sizing studies. However the GA is relatively hard to code due to its complex structure. Moreover, if the number of parameters becomes larger, the GA structure becomes more complex and the response time of GA increases quite significantly. **Dufo-Lopez and Bernal-Agustin** (2008). developed a simulation program named Hybrid Optimization by Genetic Algorithms (HOGA) based on utilization of GA in order to design different combinations of stand-alone hybrid energy systems including renewable energy sources as well as conventional diesel generator. **Lagorse, Paire and Miraoui** (2009). applied GA to economically design a multisource hybrid unit composed of PV, wind and fuel cell. **Yang, Zhou, Lu and Fang** (2008). proposed an optimal sizing method for the optimal configuration of a hybrid solar-wind system with battery storage using Genetic Algorithms. They had two major concerns whilst designing a hybrid solar-wind power generation system: the system's power reliability under varying weather conditions and the corresponding system cost. **Tafreshi, Zamani, Ezzati and Baghdadi** (2010). presented the problem of optimal sizing of hybrid solar wind system with battery storage as a multi-objective optimization problem using Genetic Algorithms. The system was designed for an isolated site in Senegal's north coast known as Potou and its principal aims were to minimize the annualized cost of the system and to minimize the loss of power supply probability (LPSP). In their work, they also investigated the influence of load profile on design. They chose three load profiles with the same daily energy. Their results clearly indicated that the cost of the optimal configuration was strongly dependent on the load profile. **Tafreshi, Zamani, Ezzati and Baghdadi** (2010), presented a methodology to perform optimal unit sizing for distributed energy resources in a micro-grid. They implemented a method based on Genetic Algorithms to calculate the optimal system configuration that could achieve a customer's required loss of power supply probability (LPSP) with a minimum cost of energy (COE). **Jemma, Hamzaoui, Essounbouli, Hnaien and Yalawi** (2013), proposed a methodology to optimize the configuration of hybrid energy system using fuzzy adaptive Genetic Algorithm. Fuzzy adaptive GA changes the mutation and crossover rates dynamically to ensure population diversity and prevent premature convergence. They obtained the optimal number of PV cells, wind turbines and batteries that ensures minimal total system cost whilst guaranteeing the permanent availability of energy to meet the load demand. They modeled the PV, wind generator and load stochastically using historical hourly wind speed, solar irradiance and load data. Their objective function to be minimized was the cost with the technical size as the constraint. **Paulitschke, Bocklisch and Bottiger** (2017). employed a GA to build and optimize a hybrid system for feeding remote locations in Senegal that included a solar generator, wind turbine, diesel generator and battery storage system. They had two objectives which were to lower the cost of the system and to reduce the CO_2 emissions. The data revealed an inverse relationship between the levelised cost and CO_2 emissions, with CO_2 emissions declining from 762.08 to 11.89 per year while levelised cost rose from 1.22 to 2.05 /KWh.

Particle Swarm Optimization

Particle swarm Optimization (PSO) is a swarm-based stochastic algorithm proposed originally by James kennedy and Russell Eberhart in 1995 which exploits the concepts of the social behavior of animals like fish schooling and bird flocking. PSO is an optimization technique based on the movement and intelligence of swarms and belongs to evolutionary computation techniques. Particle swarm is the system model or social structure of basic creature which makes a group to have some purpose such as food searching. It is a technique for population-based evolutionary simulation. Its prominence is expanding due to its quick convergence and ease of usage in single-peak and multisensory activities. It is the most widely used metaheusistic algorithm. To achieve the global optimum, each iteration stage computes the position and velocity of each particle in the swarm individually. To achieve the required outcome, each particle records two possible values namely Pbest(the best solution discovered) and swarm best (the best solution found by the entire swarm).

The input data of PSO-based methodology are the meteorological conditions, the unit prices of the projected hybrid system components including installation and maintenance costs, predefined constraints and fitness function and the values of specific PSO parameters. The process of PSO-based sizing methodology is a population based stochastic optimization procedure. Each potential solution in PSO population is called a particle. In PSO, the co-ordinates of each particle represent a possible solution associated with position and velocity vector. Each particle is initialized by a random velocity and is flown through the search space. At each iteration, particle move towards an optimum solution through its present velocity, personal best solution obtained by them so far and global best solution obtained by all particles. For example, the current position of a particle in search space at iteration 'I' is assumed as 15, 20 (15kW wind turbine, 20kW PV system) on x-y diagram. Besides, the current position of the particle having the best fitness value among all population at the current iteration is assumed as 25, 20 (25kW wind turbine, 20kW PV system). It is also assumed in PSO that all the particles in the population have great knowledge on the current positions of its neighbours and the particle having the best position. Thus the particle at 15, 20 position examines the search area and increases its current velocity on the x-axis to reach the particle with the best position at 25, 20. All the particles in the population apply the same procedure at each iteration and thus a group movement is reached with this process. The iteration procedure continues until a pre-defined termination criterion is reached.

Although both GA and PSO algorithms have excellent Efficiency with using similar iterative searching methods, the PSO has some advantages over GA. Below are some of the advantages of PSO over the GA

1. The PSO is based on simple concept involving few equations that are easy to implement in a software environment. Therefore the computation time is short and it requires few memories. However, the reliability for finding the global optimum of a search area is lower than GA-based approach. Besides, the PSO approach is less suitable than GA for problems consisting of more than three parameters as PSO is based on coordinate definition of particles and the mentioned coordinates can only be defined on x, y and z plane. For example if a PV/wind/fuel cell hybrid system is considered and only the sizes of the mentioned system is to be optimized, then the x-axis may be used to present the number of PV panels, the y-axis may present number of wind turbines and the z-axis may be related to power of fuel cell system in kW. Thus below the three components, the use of PSO can be more efficient than GA. However, if more than three components are available, it will be more preferable to utilize GA approach instead of PSO.

2. PSO is easier to implement than GA as it does not feature operator such as mutation, selection or crossover.

3. In terms of convergence and solution quality, PSO is poor in exploration as compared to GA but excels in exploitation of good solutions and has been shown to converge to good solutions quickly once the region containing the good solution has been narrowed down.

Pirhaghshenasvali and Asaei (2014). presented a paper in which a hybrid system for a practical standalone renewable energy generation system was proposed. They employed Wind, PV, Battery banks and Diesel Generators in their hybridization. The Wind PV Battery system was intended as the primary system with the diesel generator provided as a backup system. The goal of their optimization was to minimize investment cost and fuel cost while ensuring availability of the energy needed by the customers and sufficiency to meet peak demand. The design was based on solar radiation data, wind speed data and load curves and particle swarm optimization algorithm was used for optimal sizing. **Bashir and Sadeh.** (2012). argued that capacity sizing was important to fully meet demand due to uncertainty in generation of wind energy and solar PV. They formulated the algorithm for determining the capacity of wind, PV and battery energy storage system (ESS) as an optimization problem with the objective of minimizing the system cost whilst constrained to having a given reliability for a given load. This was solved using the PSO algorithm. **Bashir et al** (2012). presented a paper in which they considered a hybrid system of wind, PV and tidal energy with battery storage. They highlighted the benefits of tidal energy which is energy harnessed from rising and falling of ocean water levels as being highly predictable compared to wind and solar. They considered a 20 year plant life and optimize the design with the objective of minimizing the annualized cost of generated energy of the life of the plant, with the constraint of having a specific reliability index. They use PSO algorithm for optimization. The simulation carried out in Matlab environment revealed that in comparison to stand alone hybrid wind solar, the new system was more economical.

Saber and Venayagamoorthy (2013). Presented a paper suggesting the introduction of controllable loads with intelligent optimization as a necessity for the implementation of smart micro grids (SMG). They noted that over or under estimation of resources when considering reliability of the smart micro grid would make it not feasible, thus the optimization problem for sizing of SMG components was presented as a complex multi-objetive optimization problem considering minimization of capital cost and operations cost as objectives subject to constraints such as net zero emission, historical and wind speed and solar irradiation data and load profiles over a long period of time. They use PSO algorithm to solve the optimization problem, and an intelligent energy management system for dispatch of the resources. **Navaerfard et al**. (2010) presented an optimal sizing approach for distributed energy resources in a micro grid consisting of wind, solar hybrid system with electrolizer, hydrogen tank, fuel cell and batteries. They proposed the uncertainty of wind power alongside a reliability index as constraints and used PSO algorithm to obtain the global optimal solution.

He, Deng and Huang (2013), postulated that low carbon power technologies such as Solar- PV, wind etc are gaining a lot interest and concern worldwide, and because these technologies are mainly adopted in micro-grids, they emphasizes on the importance of considering the low carbon factor in the generation planning of micro-grids. They use the levelized cost of electricity (LCOE) analysis method to compare the variation trends of power supplies which use different energy sources to generate in the future and to build the energy price equilibrium point analysis model of high carbon energy and low carbon energy. Based on the above research, the authors developed a full life dynamic model for optimal sizing of components in an integrated power generation model. Modified particle swarm optimization was used to perform optimization. Based on the three cases considered, low carbon, high carbon and equilibrium, results show that a balanced system is most suitable for clean energy production with an equilibrium point of energy consumption and carbon consumption.

Simulated Annealing (SA)

Simulated Annealing is a non-deterministic global optimization strategy that is inspired by the process of annealing in metallurgy. It is a method of solving unconstrained and bound-constrained optimization problems. This method models the physical process of heating a material and then slowly lowering the temperature to decrease defects, thus minimizing the system energy.. Annealing involves the heating of metals to high temperatures then followed by systematic controlled cooling to encourage formation of larger crystals with fewer defects. The technique involves exposing the material heating above its crystallization temperature and then by controlled slow cooling. Heating increases the internal energy of the system and allows the atoms to move freely, and when the system is cooled, a new configuration is discovered with lower energy. SA is a good strategy for finding approximate optimal solutions where a large discrete search space is involved. At each iteration, a candidate move is randomly selected and this move is accepted if it leads to a solution with a better objective function value than the current solution. Otherwise the move is accepted with a probability that depends on the deterioration of the objective function value based on 'Metropolis criteria'. For example, the hybrid PV-wind system considered in PSO can be examined again. The current best solution in the population at iteration 'I' is assumed to be 25/20 (25kW wind turbine, 20kW PV system). Another new solution in the population is also assumed as 15/20 (15Kw wind turbine, 20Kw PV system). If this new solution has a better fitness value than the current best solution in the population, then the new solution is accepted. On the other hand, if this new solution has a worse fitness value than the current best solution in the population, then the solution may also be accepted and considered for the new population at the next iteration depending on the difference between its fitness value and the best fitness value. The annealing procedure depending on the temperature decrement allows for wide area searches by a faster temperature decrement at the beginning of the iterative process, then local area searches around the best solutions in the wide area search steps with slower temperature decrement in the next steps of the algorithm. The temperature decrement procedure is called 'cooling schedule' which is the main structure of the SA approach. The cooling schedule determines how the temperature of the system changes over time. In the beginning, the temperature is high so that the algorithm can explore a wide range of solutions, even if they are worse than the current solution. As the iterations increase, the temperature gradually decreases, so that the algorithm becomes more selective and accepts better solutions with higher probability. A simple scheduling can be obtained by dividing the current temperature by a factor which is less than 1. The acceptance criterion determines whether a new solution is accepted or rejected. The acceptance depends on the energy difference between the new solution and the current solution as well as the current temperature. The classic acceptance criterion of SA comes from statistical mechanics and it is based on the Boltzmann probability distribution which

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states that a system in thermal equilibrium at temperature T can be found in a state with energy E with a probability proportional to exp(-E/KT).

Prob (E) ≈ exp(-E/KT)

Where K is the Boltzmann probability constant. Hence at low temperatures, there is a small chance that the system is in a high-energy state. This plays a crucial role in SA because an increase in energy allows escape from local minima and find the global minimum.

Based on the Boltzmann distribution, the following algorithm defines the criterion for accepting an energy variation ΔE at temperature T

```
        If (ΔE <0)  then
        Return True
Else
        r ← generate a random value in the range (0, 1)
If      ( r <exp(-ΔE/T)) then If
        Return True
Else
        Return False
end
end
```

Finally we run the algorithm by iteratively applying the perturbation function and acceptance criterion to the current solution. The algorithm terminates when the temperature has cooled to a certain level T_{min} or when the energy of the current solution is lower than a fixed threshold E_{th}

```
T  ←  Tmax
X ← generate the initial candidate solution
E  ← E (X) compute the energy of the initial solution
    While(T >Tmin) and (E >Eth)  do
   Xnew ← generate a new candidate solution
 Enew ← compute the energy of the new candidate Xnew
    ΔE ← Xnew – E
 If accept (ΔE, T ) then
   X ← Xnew
   E  ← Enew
end ←T/α  Cool the temperature
end
return  X
```

The flow chart representing the steps in SA is shown below.

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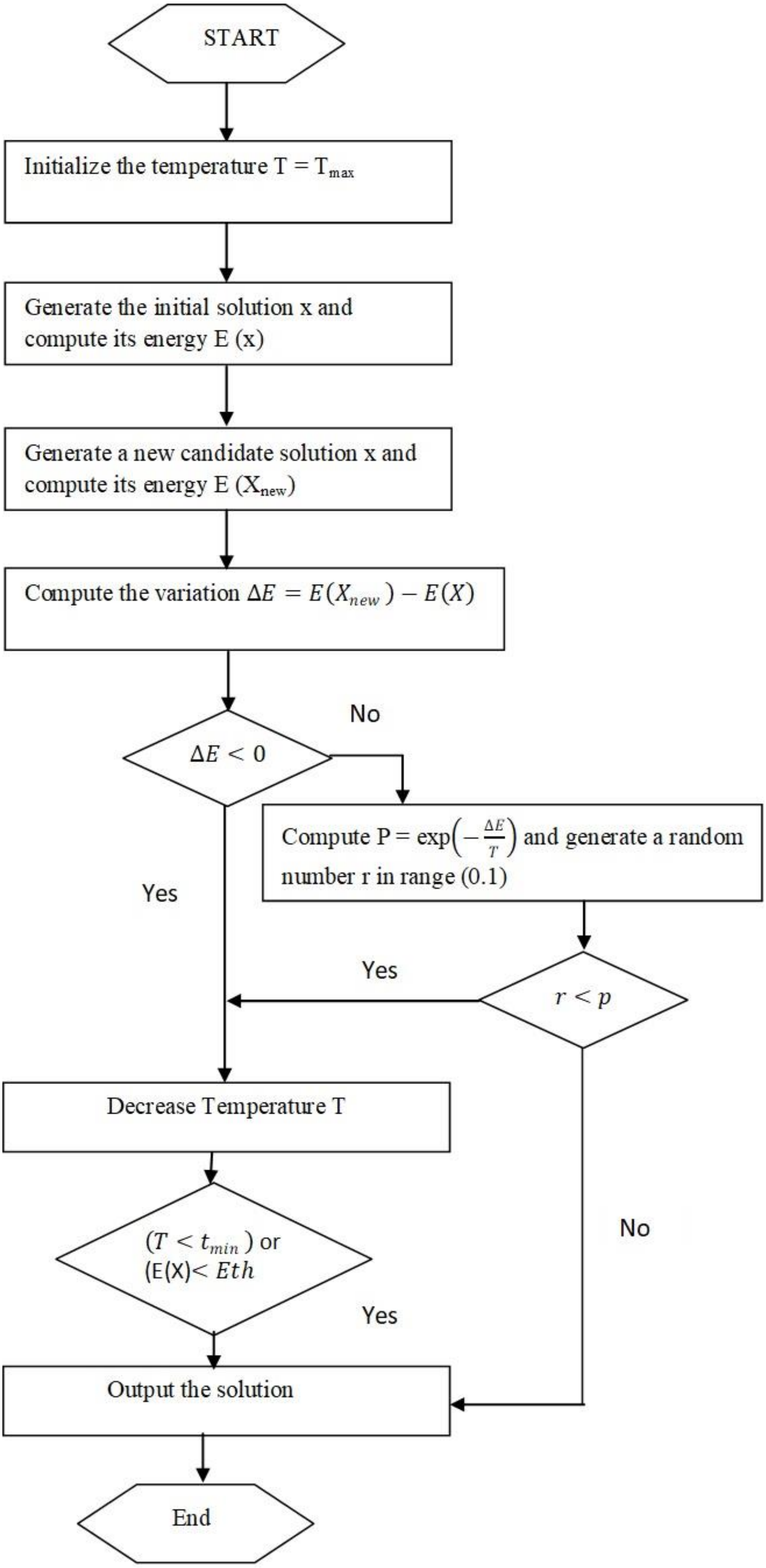

Fig 2 Flow chart showing the steps in Simulated Annealing

CONCLUSION

Hybrid Energy systems offers a reliable means of supplying power especially to developing areas that suffer from erratic power supply or areas that are not connected to the grid. It has been demonstrated that stand alone renewable energy generation is a viable alternative to grid supply or conventional fossil fuel based power generation for remote areas. Hybridizing two or more sources with complementary characteristics has emerged as an important technique for improving reliability and reducing cost of renewable energy generation in spite of the intermittency of the individual sources such as wind or solar. Hybridizing energy sources helps in providing emission-free power supply and in cases where non-renewable sources are considered, hybridizing helps to reduce the amount of fossil fuel that would have been use. Optimal sizing of the components of a hybrid system is crucial for the feasibility of the system in terms of cost, reliability and sustainability.

In this work, the various methods for optimizing hybrid energy systems have been discussed. The role of genetic operators such as crossover, mutation and selection in alleviating premature convergence is studied extensively. The concept of PSO has also been presented.

From the result of the review, the genetic algorithm (GA) and particle swarm optimization (PSO) are the most common optimization methods used for optimal sizing of hybrid energy systems due to their fast convergence rate and short computational time. Hence they have been proven to be effective and accurate.

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