Modelling, Simulation and Optimal Sizing of a Hybrid Wind, Solar PV Power System in Northern Kenya

Victor O. Okinda*, Nicodemus A. Odero**.

*Department of Electrical and Information Engineering, School of Engineering, University of Nairobi, P.O. Box 73733-00200, Nairobi –KENYA

** Department of Electrical and Information Engineering, School of Engineering, University of Nairobi, P.O. Box 30197-00100, Nairobi –KENYA

(victorokinda@gmail.com, abungu2004@yahoo.com)

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Abstract- Solar and wind, the most abundant renewable energy resources are still expensive to deploy and are unreliable as they are intermittent. It has long been postulated in open published literature that solar and wind have complementary regimes, and that their reliability can be improved by hybridization. This paper reports on the findings of research examining the problem of optimally sizing a hybrid wind and solar renewable energy power generation system.

In the research, a target site was first identified and meteorological data collected. Components of the system were then mathematically modelled from which an objective function was developed. A parallel multi-deme implementation of genetic algorithm was then used to optimize. Multiple scenarios were prepared and simulated to obtain an optimal configuration of the hybrid power system. The results obtained were validated against openly published results from real word projects. The key findings confirmed that on some locations wind and solar have complementary regimes and can thus be hybridized. To this end an optimal configuration of the system for off-grid deployment was developed with an attractive levelized cost of energy of 17 US cents per kWh. Another finding of the research decoupled resource optimal solutions from cost optimal solutions in that the least cost configuration didn't necessary maximize on the utilization of the abundant resource.

Keywords Energy storage; hybrid power systems; optimization methods; renewable energy sources; Genetic Algorithms; solar energy; wind energy

1. Introduction

In the wake of increasing oil prices, global warming and climate change, renewable energy technologies such as wind, solar, geothermal, biomass and hydro power have emerged as the green way to power our future. Geothermal, hydro power and biomass are limited by resource availability and high development costs. Wind and solar have thus been the key technologies towards realizing a green powered future. These two technologies are however faced by challenge of intermittency. A good power system however should be able to meet its demand wholly and reliably. A new emergent trend is the hybridization of renewable energy technologies with complementary characteristics. Depending on the location, good solar irradiance such as in summer, will imply poor wind speeds and in winter good wind speeds are experienced whereas solar insolation is low. On a daily distribution, wind and solar peak differently and are usually observed in complementary regimes, thus combination of the two will usually provide a better utilization factor for the available energy [1].

A hybrid wind and solar renewable energy generation system is proposed here. Battery Banks are also included to be used as energy storage. Energy storage is important in renewable energy power systems as they convert the jerky intermittent power produced into a smoother and dispatch-able form. Additionally Energy storage systems also provide ride-through capacity to renewable energy power systems when the renewable energy sources fail to meet demand. An energy storage system is usually selected depending on the application the system is being designed for. For this case, a remote town in a far-flung region of Kenya is selected.

Some of these regions have an abundance of renewable resources such as wind and solar that can be harnessed to power small remote towns and outposts in Kenya. This is thus a promising area of application as these remote towns are either powered by diesel generators which are costly to operate and maintain due to associated high fuel costs or are without power as they are usually cut off from the grid. To arrive at this optimal configuration, a parallel multi-deme genetic algorithm implementation was used for optimization.

2. Select Literature Review

Genetic Algorithms are metaheuristic search algorithms that mimic the process of evolution by natural selection. They usually start with a random generation of an initial population of chromosomes with or without domain specific knowledge. The chromosomes are represented as a data structure of binary numbers or real numbers depending on the encoding method and are parameters of possible solutions to the problem at hand. A problem specific fitness function is used to map the chromosomes into a fitness value which is a representation of the quality of the solution they represent.

Genetic Algorithm operators: Selection, Crossover and Mutation are then used to evolve the population from its current generation to the next whose average fitness value should ideally be better.

New generations are thus evolved from the knowledge of previous generations and since the fitter individuals in the population are the ones selected for crossover their good genes (good solutions) over time dominate the population and the algorithm converges to an optimum. With proper parameter selection, GA's are capable of obtaining a suitable global optimum solution.

Various variants of Genetic Algorithms exist with different subtle modifications to the original algorithm. Worth mentioning due its popularity is adaptive GA. Adaptive GA has a number of variants including fuzzy adaptive GA involves dynamic configuration of the genetic algorithm's parameters such as the mutation rate, crossover rate, or even population size depending on the status of the GA. This is in an attempt to balance and maintain precedence between exploration and exploitation. Below is a summary of literature reviewed that used Genetic Algorithms or its variants.

Yang et al. [2] had 2 main concerns whilst designing a hybrid solar-wind power generation system: the system's power reliability under varying weather conditions, and the corresponding systems cost. In their paper they proposed an optimal sizing method for the optimal configuration of a hybrid solar -wind system with battery storage using Genetic Algorithms.

Bilal et al. [3] presented the problem of optimal sizing of hybrid solar wind system with battery storage as a multi-objective optimization problem solved 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. Achieved results clearly indicated that the cost of the optimal configuration was strongly dependent on the load profile.

Tafreshi et al. [4] 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).

Jemaa et al. (2013) [5] proposed a methodology to optimize the configuration of hybrid energy systems using fuzzy adaptive Genetic Algorithms. 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 demand. They modelled 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.

3. Geospatial Resource Assessment

Technical feasibility of renewable energy generation projects are usually highly dependent on geographical location. This is because different locations have different resource potentials.

For this study, a region with strong potential for both solar and wind is preferable. The SWERA GIS toolkit available at http://en.openei.org/wiki/SWERA/Data is used to zero in on a location with promising solar and wind potential.

The German Aerospace Centre (DLR) Global Horizontal Irradiance Layer is first overlaid over the digital map.

From the geospatial resource assessment exercise, it is clear that a suitable location for a pilot project on hybrid renewable wind and solar PV generation would be need to have great potential for both solar and wind power generation. As already identified in the SWERA study for Kenya [6] areas around Lake Turkana, East and North East of Kenya have incredible potential for solar PV generation. The area around Lake Turkana and some areas of the Rift Valley and coastal region have significant potential for wind

Fig. 1. Base Map of Kenya

power development. Having overlaid both resource maps onto the base map and filtered for only areas with significant wind and solar resource potential it emerges that the Lake Turkana area would be suitable for a hybrid wind and solar generation project. Coincidentally, a synoptic weather station exists in this region at Marsabit and a typical meteorological year (TMY) dataset exist.

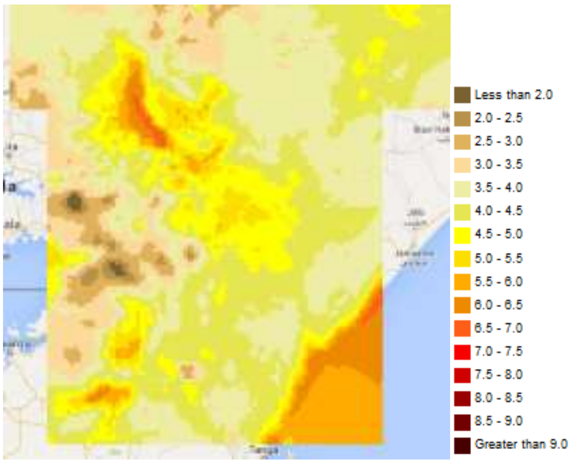

Fig. 2. DNI Map of Kenya

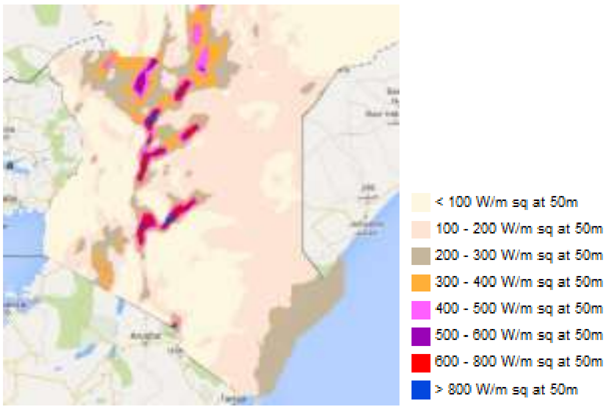

Fig. 3. Kenya Wind Atlas at 50m above ground level

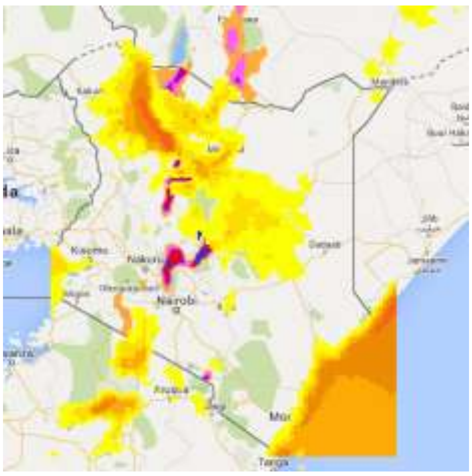

Fig. 4. Geospatial overlay of commercially viable wind and solar potential in Kenya

4. System Component Modelling

4.1. Hybrid System Model

The hybrid power system consists of an array of solar photovoltaic generators, wind turbine generators, and a battery bank and associated power regulation and conversion accessories, protection and switching equipment. Only the generation components are modelled in this study as they represent the key plant components.

Figure below shows the system's simplified single line diagram. Hybridization is carried out at the DC bus independent of phase and frequency constraints that would need to be overcome on an AC bus.

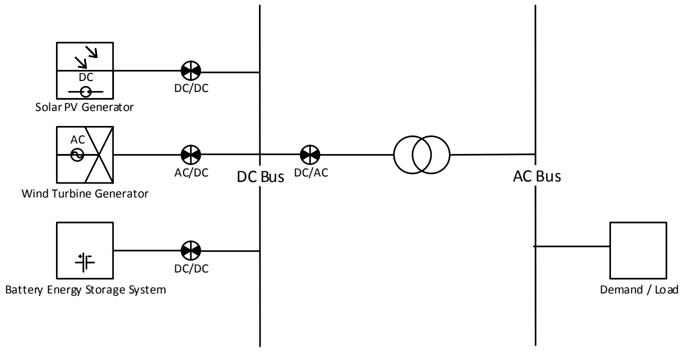

Fig. 5. Model of the hybrid system

4.2. Solar PV Model

According to Xu et. al [10] assuming the PV arrays are equipped with MPPT trackers then for modelling simplicity, equation (1) below sufficiently models the array power output.

$$P_{PV}(t) = f_{PV} P_{PVR} \frac{G(t)}{G_{STC}} (1 + \alpha_T (T(t) - T_{STC}) \quad (1)$$

Equation *(2)* , derived from above was used to model the total instantaneous power generation from solar for a total of N_{PV} units.

$$P_{PV}(t) = N_{PV} f_{PV} P_{PVR} \frac{G(t)}{G_{STC}} (1 + \alpha_T (T(t) - T_{STC}) \quad (2)$$

Where,

The output power the panel array at time instance t is $P_{PV}(t)$, the rated power of which is P_{PVR}, the derating factor considering shading and wiring loses is f_{PV}. The inputs to the model are the temperature at time instance t represented by $T(t)$ and the solar radiation represented by $G(t)$. G_{STC} and T_{STC} respectively are the solar radiation and temperature for the panel at standard test conditions. α_T is the temperature coefficient which is provided by the manufacturer's datasheets.

The de-rating factor f_{PV} is determined from solar PV modeling best practice [7]. It is assumed in this research that shading is negligible and hence is not accounted for in determination of f_{PV}. This is somewhat true for utility scale PV applications as the layout can be such that shading from adjacent panels is eliminated or minimized by proper spacing, whereas that due to features in the topography of the surrounding site avoided by proper site selection and preparation. The remaining contributing factors are summarized in the table below.

Table 1. Solar PV modelling parameters

Parameter	Value
AC wiring	99.00%
Array soiling	95.00%
DC wiring	98.00%
Diodes and Connections	99.50%
Inverter and transformer	92.00%
Mismatch	98.00%
Panel de-rating factor, f_{PV}	82.68%

4.3. Wind Turbine Generator Model

Xu et. al. [10] proposed to model the power output from a wind turbine generator using the Eq.(3) which governs the power output from a single wind turbine and Eq.(4), the power output from the assembly of wind turbines. Wake losses were not considered for simplicity.

$$P = \begin{cases} 0 & 0 \le v_u < v_{in} \\ P_r \dfrac{v_u - v_{in}}{v_r - v_{in}} & v_{in} \le v_u \le v_r \\ P_r & v_r \le v_u < v_{out} \\ 0 & v_u \ge v_{out} \end{cases} \qquad (3)$$

$$P = \begin{cases} 0 & 0 \le v_u < v_{in} \\ N_{WTG} P_r \dfrac{v_u - v_{in}}{v_r - v_{in}} & v_{in} \le v_u \le v_r \\ N_{WTG} P_r & v_r \le v_u < v_{out} \\ 0 & v_u \ge v_{out} \end{cases} \qquad (4)$$

Where

P_r is the rated power output of the wind turbine,

$C_p(v_u)$ is the coefficient of performance of the turbine, simplistically modelled from the turbine datasheet to be a function of wind speed only,

v_u is the prevailing incident wind speed adjusted to mast height,

v_{in} is the cut-in speed of the wind turbine taken from the turbine datasheet.

v_r is the rated speed of the turbine taken from the turbine datasheet.

v_{out} is the cut-off / out speed of the turbine taken from the turbine datasheet.

4.4. Battery Model

An advanced Lead Acid battery is proposed. The battery's state of charge (SOC) is an important parameter modelled. It is the ratio of the amount of energy stored in the battery to its capacity at any given instance. Diaf et. al [54] determined the SOC as;

$$SOC(t) = SOC(t-1)(1 - \frac{\sigma \Delta t}{24}) + \frac{P_{WTG}(t) + P_{PVG}(t) - P_L(t)}{C_{BESS} V_{BESS}} \qquad (5)$$

The equation above was used to update the state of charge of the BESS at the end of each time step.

Where the battery self-discharge rate is given by σ and Δt is the length of the time step, C_{BESS} is the BESS capacity in Ampere hours and V_{BESS} the terminal battery voltage.

The State of charge is an energy ratio hence cannot be plugged in directly to a power flow equation. It would be necessary to multiply it with the BESS energy rating. For simplicity in calculation, the researcher makes an assumption here that the BESS is able to deliver constant power over the duration of the time step (1 hour), the internal self-discharge rate is also ignored as it is negligible relative to the other quantities (depends on the battery technology but typically assumed at 0.2% per day for generic models [8]), while not the case in reality it greatly simplifies computational requirements without adversely affecting the results. With this assumption, the power rating and the energy rating in a time step are equally treated. Thus the corresponding available power flow from the BESS can be determined as;

$$P_{BESS}(t) = (SOC(t) + DOD_{MAX} - 1) \times P_{BESS\_rated} \qquad (6)$$

In this expression, DOD_{MAX} is the maximum depth of discharge and is the equivalent of the absolute minimum state of charge for the proper functioning of the BESS. It varies with the BESS technology used.

The BESS charge-discharge algorithm can thus be written in the form of the pseudo code below;

Table 2. Psuedocode for charge / discharge algorithm of the BESS

1. If $(P_{PVG} + P_{WTG}) > P_D$
   a. Then , all demand has been met, extra power generated to charge BESS

b. Update SOC as;

$$SOC(t) = SOC(t-1)\left(1-\frac{\sigma\Delta t}{24}\right) + \frac{\eta_{conv}*RTEF*(P_{PVG}+P_{WTG}-P_D}{N_{BESS}*P_{BR}}$$

2. Else if $(P_{PVG} + P_{PWTG}) < P_D$
   a. Check if Demand will be met with BESS addition
   b. If

$$(P_{PVG} + P_{PWTG} + \eta_{conv} N_{BESS} P_{BR} (SOC(t-1) + DOD_{max} - 1)) > P_D$$

   c. Demand has been met

$$SOC(t) = SOC(t-1)\left(1-\frac{\sigma\Delta t}{24}\right) - \frac{(P_{PVG}+P_{WTG}-P_D}{\eta_{conv}*N_{BESS}*P_{BR}}$$

   d. Update SOC as
   e. Provided that maximum Depth of Discharge is not violated: thus
      i. If $SOC(t) < 1 - DOD\_max$ then
      ii. Revert and declare Demand not met, overwrite SOC as;

$$SOC(t) = SOC(t-1)\left(1-\frac{\sigma\Delta t}{24}\right)$$

3. Else
   a. Demand not met
   b. Nonetheless , update SOC on account of self-discharge as

$$SOC(t) = SOC(t-1)\left(1-\frac{\sigma\Delta t}{24}\right)$$

4.5. Demand Model

A hypothetical load model was used. It was derived from data made available to the researcher by the national power utility, Kenya Power. The data covered the month of September for the years 2009 to 2012. It was used to derive a typical daily load curve for a metropolitan area. For improved accuracy, two load curves are used one to represent typical weekdays and one to represent typical weekends and holidays. A base consumption figure is derived from the data above and adjusted to reflect growth as covered in [9].

Fig. 6. Weekday demand curve

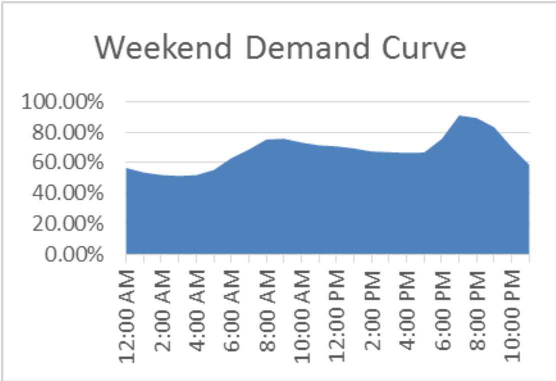

Fig. 7. Weekend demand curve

5. Optimal Sizing Algorithm

5.1. Objective Function

From the models above, the cost function is derived. It is desired that a technical feasible system is sized at a minimum cost. The objective function is thus in this case an economic cost function that is constrained with technical boundary conditions. These boundary conditions are discussed in the next section. The optimization problem is modelled around one technical index the Loss of Power Supply Probability (LPSP) to model system reliability and one economic index the Levelized cost of Energy (LCOE) to model cost of energy produced by the system. These are from here on referred to as the reliability objective and the cost objective.

5.2. The Reliability Objective

The Loss of Power Supply Probability (LPSP) introduced in the literature review is used here. LPSP is the probability that over a certain period of study, the power demand is not fully met by the generated power. Mathematically it is represented as shown below

$$LPSP = \frac{\sum_{i=1}^{N}[P_L(t_i) - P_G(t_i)]}{\sum_{i=1}^{N} P_L(t_i)} \tag{7}$$

The period of consideration is one year in time steps of an hour, hence $N = 8760$

In the equation above, $P_L(t_i)$ represents the load at a given time step on hour i .

In the same definition $P_G(t_i)$ represents the energy generation from the hybrid power system. In actual implementation, $P_L(t_i)$ is generated from daily load curves for weekdays and weekends and factors in monthly anticipated load growth as deduced from the 10 year power sector expansion plan for Kenya covering the years 2014 – 2024 [9]. This is covered under the load model above.

$$P_G(t_i) = \begin{cases} P_{WTG}(t_i) + P_{PVG}(t_i) + P_{BESS}(t_i) & \ldots case\ 1 \\ P_{WTG}(t_i) + P_{PVG}(t_i) & \ldots case\ 2 \\ P_{WTG}(t_i) + P_{PVG}(t_i) - P_{BESS}(t_i) & \ldots case\ 3 \end{cases} \quad (8)$$

Case1, applies when the total power generation from both the wind turbines and solar PV cells is less than the load is. The shortfall in power is then met by the stored energy in the batteries.

Case 2, applies when the total power generation from both the wind turbines and solar PV cells is equal to the demand, and

Case 3, applies when the total power generation from both the wind turbines and solar PV cells is greater than the demand, in this case, the surplus power is used to charge the batteries.

$P_{WTG}(t_i)$, is the power generated by the wind turbines in the time step i. This is expressed as in eq.*(4)* . $P_{PVG}(t_i)$, is the power generated by the solar photovoltaic generator in the time step i. This is expressed as in eq.*(2)* . $P_{BESS}(t_i)$, is the power flow equation from or to the battery energy storage system in the time step i. This is expressed as in equation *(18)*

Eq.*(8)* can be further simplified using the Heaviside step function as;

$$P_G(t_i) = P_{WTG}(t_i) + P_{PVG}(t_i) + 2.P_{BESS}(t_i).(H(P_L - P_{WTG} - P_{PVG}) - \tfrac{1}{2}) \quad (9)$$

From the definition of LPSP, it is clear that an LPSP of 1 indicates that the load is never met whereas that of 0 indicates the load is fully met. The reliability objective is passed as an inequality constraint in the minimization of the cost objective. An LPSP of 5.0% corresponding to approx. 500hrs in a year of unmet demand is chosen as the low threshold for any solution to be valid.

5.3. The Cost Objective

The Levelized Cost of Energy (LCOE) introduced in chapter 1 is used here. The LCOE is a convenient metric for measuring the overall cost competitiveness of a generating technology. It represents the overall project cost both in terms of overnight capex, operation and maintenance cost and discounted negative cash flows, inter alia over the project life divided by the total energy generated by the project over its entire life and is presented as dollars per KWh. In deriving the LCOE the following consideration are made:

Costs; The initial invested capital, operating and maintenance costs (fixed and variable), Financing costs, insurance costs, Taxes, Lifecycle or Major replacement costs, decommissioning costs. Etc.

Rebates and Incentives; Tax credits, Accelerated depreciation (MACRS), Incentives .etc.

Energy; Annual energy production, annual degradation, system availability.

The LCOE is then expressed as;

$$LCOE = \frac{\sum Life\ Cycle\ Costs(USD) - \sum Life\ Cycle\ Rebates\ (USD)}{\sum Life\ Cycle\ Energy} \quad (10)$$

Moreover, the LCOE can be expressed either as nominal LCOE or as real LCOE where the real LCOE has been inflation adjusted to cater for the macroeconomic factors. In this evaluation the LCOE has not been inflation adjusted as its principle purpose is to be a fitness function for comparing multiple options in a similar setting which implies the macroeconomic environment remains the same hence no need for the adjustment. Furthermore, for efficiency in execution of the algorithm a simplified version of the LCOE is used as an objective function. The simplified LCOE does not factor in financing costs, insurance costs, future replacements and degradation as it is thought that these differences among the options will be marginal yet the savings in terms of computational resources will be substantial. The LCOE used is thus expressed as:

$$LCOE = \left[\frac{CC \times CRF + FOM}{8760 \times CF}\right] + FC + VOM \quad (11)$$

Where CC refers to capital costs in USD/ KW and is deduced as shown in below.

$$CC = \frac{N_{PV}}{N_{TIC}} CC_{PV} + \frac{N_{WT}}{N_{TIC}} CC_{WT} + \frac{N_{BESS}}{N_{TIC}} CC_{BESS} \quad (12)$$

Where;

N_{TIC} is the total installed capacity in kW,

N_{PV} is the PV installed capacity in kW,

N_{WT} is the installed capacity of wind turbines in kW,

N_{BESS} is the power rating of the installed battery energy storage units,

And CRF is the capital recovery factor. The capital recovery factor is the ratio of a constant annuity to the present value of receiving that annuity for a given length of time. In this evaluation CRF has been based on a nominal discount rate as opposed to a real discount rate as the researcher has settled for evaluation of a nominal LCOE. CRF is calculated as shown in the equation below;

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \tag{13}$$

Where the nominal annual discount rate is i and n is the project life in years.

The other key cost consideration is the operations and maintenance costs (O&M). O&M is divided into Fixed and Variable components. The Fixed Operations and Maintenance costs, FOM in eq.*(11)* refers to those O&M costs that relate to the installed capacity of the plant and has the units of USD/kW.

$$FOM = \frac{N_{PV}}{N_{TIC}} FOM_{PV} + \frac{N_{WT}}{N_{TIC}} FOM_{WT} + \frac{N_{BESS}}{N_{TIC}} FOM_{BESS} \tag{14}$$

From which;

N_{PV} , N_{WT}, N_{BESS}, and N_{TIC} , retain their definitions from eq.*(12)* above.

The fixed O&M cost associated with PV technology are represented by FOM_{PV}.

The fixed O&M cost associated with wind turbines are represented by FOM_{WTG}.

The fixed O&M cost associated with battery energy storage technology are represented by FOM_{BESS}.

The other component of the Operations and maintenance costs, the Variable O&M or VOM as in eq.*(11)* is the O&M component relative to the amount of energy generated by the power plant. The Variable O&M costs are defined in a similar manner to eq.*(14)*. Thus;

$$VOM = \frac{E_{PV}}{E_{TIC}} VOM_{PV} + \frac{E_{WT}}{E_{TIC}} VOM_{WT} \tag{15}$$

From which;

E_{TIC} is the total energy **generated** in the plant life in kWh, thus

$$E_{TIC} = E_{PV} + E_{WT} \tag{16}$$

E_{PV} is the PV generated energy in kWh,

E_{WT} is the energy generated by the wind turbines in kWh,

The Operations and maintenance costs relating to the battery storage unit are all modelled as Fixed O&M. This approach allows for simplicity in evaluation of the objective function. It is also the researcher's postulation that the variable component in the O&M cost for the battery energy storage system is negligible compared to the fixed component.

The Fuel Cost is represented by FC. In this assessment since generation is based on wind and solar, for which the energy sources are wind and solar irradiation respectively and which are free and abundant in nature, the fuel cost component is thus zero and is eliminated from the implemented cost objective function.

CF in eq.*(11)* refers to the plant capacity factor, evaluated as

$$CF = \frac{Total\ Energy\ Generated\ annually\ by\ HRES(kWh)}{Total\ Installed\ Capacity\ of\ Power\ Units\ (kW) \times 8760} \tag{17}$$

$$CF = \frac{Energy_{PV} + Energy_{WT} + Energy_{BESS}}{(N_{TIC}) \times 8760} \tag{18}$$

The cost objective function to be minimized can thus be presented in full as:

$$minimize\ LCoE,$$

$$where\ LCOE =$$

$$\frac{\left(N_{PV}CC_{PV} + N_{WT}CC_{WT} + N_{BESS}CC_{BESS}\right) \times \left(\frac{i(1+i)^n}{(1+i)^n - 1}\right)}{Energy_{PV} + Energy_{WT} + Energy_{BESS}} + \frac{\left(N_{PV}FOM_{PV} + N_{WT}FOM_{WT} + N_{BESS}FOM_{BESS}\right)}{Energy_{PV} + Energy_{WT} + Energy_{BESS}} + \frac{VOM_{PV}E_{PV} + VOM_{WT}E_{WT}}{Energy_{PV} + Energy_{WT}}$$

$$subject\ to\ Boundary\ Conditions\ defined\ below.$$

5.4. Boundary Conditions

These are imposed on the proposed optimal solutions to ensure adherence to physical feasible limits and safe operating conditions of the power plant. The following conditions below are considered;

That the reliability objective is met, an inequality constraint is defined as;

$$LPSP_i < 0.05 \tag{19}$$

A configuration i is only a viable candidate solution if its Loss of Power Supply Probability (LPSP) is less than 5%. This corresponds only 500 hours annually of unmet demand, much better than the existing distribution grids nationally.

Maximum installed capacity is benchmarked to the demand. A peak demand of 2 MW after factoring load growth over a 20 year period is considered. A suitable system configuration would then be sought to supply this peak demand at the least cost. Sizing constraints are also applied on the individual generation technologies.

Option 1 – Land Size based Constraints

The number of wind turbine units is constrained by consideration of losses due to wake effect. Thus as developed by [10], for a region with area S_1, length L, and width W, the maximum number of wind turbines that can be installed is then evaluated as

$$N_{WT} \leq \left[\frac{L}{L_M d} + 1\right] \times \left[\frac{W}{W_M d} + 1\right] \qquad (20)$$

Where, L_M is a multiplier between 6 and 10 and W_M is a multiplier between 3 and 5.

N_{WT} is evaluated to 14 units assuming a 10 acre piece of land.

The maximum number of PV panels will also be constrained by the size of the land acquired for the project. Thus assuming a land area S_A, and a PV panel size S_{PV};

$$N_{PV} \leq \frac{S_A(1-\alpha_{BOP})}{S_{PV}} \qquad (21)$$

The ratio of land size requirements of the balance of plant to the whole plant is represented by the factor α_{BOP}. This based on research documented in [11] has been evaluated at around 0.276.

This evaluates to 117,430 units based on a 10 acre parcel of land.

Minimum installed capacity is set as a lower bound of zero indicating that at least some capacity must be installed.

Battery charge/ discharge constraints are handled using the state of charge. There is a correlation between the state of charge and a battery's state of health. The higher the minimum state of charge, the more cycles a battery in proper operating conditions has. The charge / discharge constraints of the battery have been modelled into the performance objective function.

The number of battery units N_{BAT}, Number of installed panels N_{PV} and number of installed wind turbines N_{WT} are all bound as positive integers. This ensures only true hybrid systems with battery storage are considered.

Option 2 – Algorithm Evaluated Constraints

A second set of constraints is also applied. These constraints are engineered to constrain the optimization algorithm to resolve to minimum in less time.

The Matlab code written to achieve this is in the appendix. The pseudocode is listed below;

Table 3. Pseudocode for evaluation of boundary conditions, option 2

1. Set BESS units to 0
2. Run optimal sizing algorithm with random but reasonable upper bounds for wind and solar (base case assumptions used)
3. Iterate through 8760 time steps to work out wind and solar potential
4. Calculate approximate lower bounds using;
5. $Solar_{LB} = \frac{SP_{PVC}(1-LPSP)\times P_{LMAX}}{SP_{PVC}+SP_{WTC}}$
6. $Wind_{LB} = \frac{SP_{WTC}(1-LPSP)\times P_{LMAX}}{SP_{PVC}+SP_{WTC}}$
7. $BESS_{LB} = LPSP * P_{LMAX}$
8. Calculate approximate upper bounds using a scale factor of 10 as;
9. $UB = LB * SF$

The matrix of lower and upper bounds as determined via this method are listed below

Table 4. Boundary conditions

Case	DSM	Trk	Lower Bounds			Upper Bounds		
			S	W	B	S	W	B
D	No	No	1,975	4	7,879	19,750	40	7,890
E	Yes	No	2,438	4	3,230	24,380	40	32,300
F	Yes	Yes	3,041	3	2,103	30,410	30	21,030
S – Solar, W – Wind, B - BESS								

Base Case

As the trivial solution would involve, scaling a generation and storage sources to match the load plus a margin, upper constraints are set on the installed capacities of the solar PV generation units, wind turbine generation units and battery storage system as below;

The maximum Number of wind turbines, is set to the 1.2 times the maximum demand divided by the rated capacity of a single unit. This evaluates to 10 units.

The maximum number of PV panels is set to 2 times the maximum demand divided by the rated capacity of a single unit. This evaluates to 16000 units.

The maximum number of battery units is calculated at 1 times the maximum demand divided the rated power delivery in a single hour of each unit. This evaluates to 23809 units.

Table 5. Base case configuration

Base Case Assumptions (No. of units)		
Solar	Wind	BESS
16,000	10	23,809

6. Results

Multiple scenarios were simulated in this work in an attempt to find an optimal solution to the problem of sizing a hybrid renewable energy power system. The results have been documented and discussed in the previous chapter and are here below summarized ahead of drawing a conclusion to the work. Three control scenarios were set up; the base cases A, B and C and were found to be suboptimal as expected. In these control cases, a configuration of 16000 PV modules, 10 wind turbines and 23,809 battery units was used. Further, scenario B included simulation of a demand side management scheme, whereas scenario C included simulation of a demand side management scheme as well as PV units mounted on a single axis, sun tracking racking system. Scenarios D, E and F were the results from the optimal configuration of the hybrid renewable energy power system based on scenarios A, B and C respectively.

Table 6. Optimization results

		Wind (kW)	**Solar (kW)**	**BESS (kWh)**	**LCOE ($/kWh)**
Scenarios	**A**	4000	2500	2000	NE†
	B	4000	2500	2000	NE
	C	4000	2500	2000	31.9
	D.1	1115	8250	6601	21.51
	D.2	5078	3500	5614	30.03
	E.1	1708	6250	2708	28.26
	E.2	494	3250	9879	17.76
	F.1	2762	3750	1763	28.02
	F.2	494	3250	7968	17.62

† NE – Not Evaluated, as the technical reliability condition of LPSP < 0.05 was not met.

7. Validation and Discussion

The results obtained were validated by comparison with the Transparent Cost Database (TCD) published by openei.org. The transparent cost database is an initiative of the US department of Energy in association with the National Renewable Energy Laboratory (NREL). It is a public transparent database of program costs and performance estimates for energy efficiency and renewable energy programs that have been published in open literature. It has collated cost information from nearly 500 different sources in the last decade or so and is an authoritative benchmarking tool used in industry by project developers, investors, financiers, policy makers and regulators.

Table 7. Comparison with the Transparent Cost Database (TCD)

		Research Results	**Adjusted TCD Nominal Case**	**Adjusted TCD Worst Case**
Scenarios	A	-	21.75	41.54
	B	-	21.75	41.54
	C	-	21.75	41.54
	D.1	21.51	13.96	25.03
	D.2	30.03	22.49	42.90
	E.1	28.26	13.83	25.33
	E.2	17.76	17.25	31.04
	F.1	28.02	17.61	33.16
	F.2	17.62	16.80	30.22

Table 6 documents the Levelized cost from the various plant layout options simulated. Three layouts; cases A, B and C are presented as base cases. Cases D, E and F are optimized configurations. Case A, the base case is as configured in Table 5. Case B improves the base case by simulating the effects of implementing a Demand Side Management scheme. The actual implementation of the scheme is not covered in the work but the desired effect of aligning the demand to the power supply is simulated. Case C further improves the specific energy yield of the PV units by simulating a single axis tracker mounting solution which desirably improves the energy for a marginal increase in OPEX and CAPEX which is also factored in. Scenarios D, E and F are optimal configurations of A B and C respectively. Further under each scenarios D E and F, two approaches are taken; approach 1 constraints the simulation algorithm using a separate algorithm to work out resource potential and strictly enforces a reliability requirement of LPSP < 0.05. Approach 2 constraints the simulation algorithm to the land size of 41000 square meters but as a trade-off lowers the LPSP requirement to LPSP < 0.1. Approach 1 is geared towards finding a long term solution with reliability pertinent over cost whereas approach 2 is geared towards finding a medium term solution where it is anticipated that the national grid will expand to the area in the medium term, cost is pertinent over reliability. The LCOE is then calculated according to Equation (11) and is the key index used for the optimization process.

It is not easy to directly compare the results obtained with the LCOE values in the TCD for a number of reasons. First, the TCD does not have records of hybrid renewable energy power plants and as such any comparative metric has to be derived from the measured and documented data of the TCD. Second, the concept of energy storage is quite different from energy generation and decoupling its contribution to the LCOE from that of the generation sources is not easy. In fact other scholars and research organization have now developed a new term; levelized cost of storage to adequately measure the cost of storage. Nonetheless, as the TCD is best open documented cost database that is freely available, an attempt has been made by the researcher to determine the quality of results obtained by comparison of these to derived metrics from the TCD. This information is presented on Table 7. The TCD Nominal Case‡ is the LCOE derived from average LCOE values of wind and solar generation from the TCD and weighted in the same proportion as the scenario to which it is being compared. The TCD worst case is the LCOE derived from the weighted average of maximum LCOE values of wind and solar generation from the TCD, weighted in the same proportion as the scenario it is being compared to. As the derived TCD corresponding LCOE values do not factor in storage, the actual corresponding LCOEs if calculated from the TCD to factor in storage would be worse. A second pair of derived metrics attempt to include the influence of energy storage on the LCOE value from the TCD. Since the overnight capital cost component of the energy storage as a percentage of the total project overnight capital cost is known, this factor is used to dilute the quality of the derived LCOE. The two columns adjusted nominal LCOE and adjusted worst case LCOE provide this information. The obtained results can now be compared against the adjusted nominal and worst case LCOE. With the exception of scenario E.1 all the results lie within the bounds of the nominal and the worst case LCOE as derived from the TCD. These findings satisfactorily validate the results obtained from this research.

8. Conclusion

Three optimal configurations from three scenarios simulated have been obtained. The system components were successfully modelled and an objective function developed. The objective function developed was a two-fold objective, to minimize the loss of power supply probability (LPSP) and the levelized cost of energy (LCOE) two parameter representing the reliability and cost objectives. The objective function was then minimized by a parallel genetic algorithm from which process various optimal sizing configurations of the plant were obtained. Multiple scenario analysis was carried to determine the most optimal configuration. A total of 9 scenarios were evaluated.

The first conclusion drawn based on the results of this work is that it is feasible to develop a hybrid renewable energy system at certain locations e.g. Marsabit in Kenya. It was observed that at locations where wind and solar had complementary regimes, it was possible to optimally size the individual components of the plant to meet a certain reliability requirement.

It was also concluded as can be observed from the results of the land size constrained simulations that a higher reliability requirement was achievable at a higher cost. Most of the scenarios with a lower reliability requirement (10% LPSP) resulted in lower levelized cost of energy of less than 20 US cents per kWh, whereas the best scenario with a high reliability requirement (5% LPSP) resulted in a levelized cost of energy of 21.51 US cents per kWh.

Another interesting conclusion drawn is that a resource optimal configuration does not necessarily equal a cost optimal configuration where the cost of utilizing the different resources are not the same. It was observed that in a scenario where demand side management was simulated to optimize solar utilization and the solar PV modules themselves mounted on a sun tracking racking system, the resulting optimal configuration optimizes the utilization of solar energy but does not yield the lowest LCOE as solar PV systems were more expensive than wind turbines. The clear conclusion in terms of the way forward seen from the results is that a cost optimal system is one that optimally utilizes the cheapest resource to exploit. This is corroborated by the finding that wind intensive configuration resulted in lower LCOE than solar intensive configurations.

On the algorithm implementation and simulations, it was observed severally, and conclusions can be drawn that a parallel multi-deme genetic algorithm implementation, was better than a similar control experiment run in a serial generic GA in diversity of individuals in a search space and its exploration. This was measured by observing the average distance between individuals which was higher in the multi-deme parallel GA as compared to the serial generic GA. On the quality of the final solution though, clear conclusions could not be drawn on which was better as they both converged to approximately similar solutions.

From the results obtained, scenario F.2 is proposed. The optimization results are based on wind and solar resource data from the meteorological station at Marsabit located at 2.3° north and 37.9° East at an elevation of 1345 masl and the proposed plant will be located within a 30 km radius. The plant will comprise of a solar PV generation module with 1976 PV modules totalling a peak installed power of 494 kWp; a wind turbine generation module comprising 13 wind turbine generators with a total installed capacity of 3250 kW and a battery storage array comprising of 94,856 units of advanced lead acid batteries with a total energy storage capacity of 7968 kWh. The PV arrays are installed in a single axis sun tracking racking system and a demand side management scheme is in place. The whole plant will occupy a land area of 41,000 sq. meters, however in practical

‡ Not included in table[] due to space constraints.

implementation due to consideration of wake effect in siting the wind turbines and shading effects in siting the solar array, it is unlikely that a contiguous land mass of that area is sufficient or practical. This introduces a new problem and a great direction of future research of the optimal siting of wind turbine and solar arrays in a hybrid wind solar power generation system. Even though this option has an LPSP of only 10%, it is by far the most cost effective resulting in an LCOE of 17.62 US cents per kWh. It could further be improved with grid storage or back up to the grid, but this has been left as a proposition for further work.

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