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MultiObjective Optimal Sizing of Wind PV Hybrid Energy System using Genetic Algorithm

John Nduli*[1], Stanley Kamau[2] and Evan Murimi[3]

[1]*Department of Mechatronics Engineering, Pan African University Institute for Basic Sciences, Technology and Innovation (PAUISTI), P.O. Box 62000–00200, Nairobi, Kenya.*

[2]*Department of Electrical and Electronics Engineering, Jomo Kenyatta University of Agriculture and Technology (JKUAT), P.O. Box 62000–00200, Nairobi, Kenya.*

[3]*Department of Mechatronics Engineering, Jomo Kenyatta University of Agriculture and Technology (JKUAT), P.O. Box 62000–00200, Nairobi, Kenya.*

**Corresponding Author - Email: yohanaizraeli@gmail.com*

Abstract Electricity is an important resource, required for continued development and improvement of the world. However, access to electricity is a problem within various regions of the world, for example Africa. Renewable Energy Systems (RES) provide a viable source of electricity for regions that are not connected to the grid. However, sizing of the components required to convert these renewable sources to energy is still an active area of research. In this paper, the correlation between the power produced by the Renewable Energy System and the cost of the system is used to determine the components to choose. This correlation is materialized as the Excess Power Supply Probabilty, which is combined with the Low Power Supply Probability of a system to form a multiobjective cost function. The novel approach is then compared with another multiobjective cost function used in research, and is found to perform better in optimizing for cost, while also providing better flexibility to the designer.

Keywords Genetic Algorithm, RES, solar, wind

1. Introduction

Electricity is considered an important requirement for the future economic and social development of the world. However, access to electricity is still a problem is some regions, for example Africa [1], where two in every three people have no access to electricity, with some countries like Chad, Somalia and Uganda having access levels as low as 5% [2]. The regions that have access to power also frequently succumb to power failures, this being considered as one of the biggest challenges facing businesses in Kenya [3]. Furthermore, increased dependence on fossil fuels like coal leads to environmental degradation [4] and pollution, which is considered a global issue. A potential solution for this is to use Renewable Energy Sources (RES) to complement traditional power sources or in regions with no access to the grid, to act as an alternative. Renewable Energy Systems are systems that generate energy from renewable sources such as wind, biomass, solar (solar-thermal and PhotoVoltaics) and geothermal heat [5]. This paper will focus on wind and solar (PhotoVoltaic). Wind Energy is farmed either in small scale or large scale. Large scale wind turbine farms can cause an adverse effect of the environment as found by Tummala et al. [6], when if 10–15% of the global energy is supplied by these, an increase in land temperatures by $1°C$ will occur. Furthermore, distributed systems have been found to work well in large sparsely populated regions (as is the case in rural Africa) [7] and are a good option for sustainable energy. This is because they have significantly low operation costs, can be sized to serve the required load and will reduce migration to urban centres [7].

While developing and designing RES systems, there are various problems that need to be optimized. These include the quality of power (frequency stability, voltage, harmonics), reliability, efficiency, dimensions and cost [8]. In order to select the best parameters, various heuristic algorithms have been used for optimization [9].

The optimization algorithms are classified into complete and approximate solutions [10]. Complete solutions offer the global optimal solution but have exponential computation time, making them impractical for use in energy optimization for online use. For offline use, they may end up being too costly and time intensive while computing the best solution. Thus, approximate solutions are preferred. These approximate algorithms include: genetic algorithms [11], [12], Particle Swarm Optimization [11] and Simulated Annealing [13]. The results from these solutions have been found to be good enough for use in various optimization problems, and computation is not expensive. Ekren et al. [13] used simulated annealing together with a single objective cost function that catered for power reliability. Jyoti B. Fulzele [12] used genetic algorithm, with a single objective cost function that minimized the net present cost. This cost comprised of the capital cost, replacement cost and operational costs of the components. Nafeh et al. [14] also used genetic algorithm, but had a multiobjective cost function that minimized the cost and improved the system reliability. Particle Swarm Optimization has also been used by researchers [15], [16], with Hakimi and Moghaddas-Tafreshi [16] also using a single objective function that minimized the net present cost. However, the use of single objective functions for cost fails to include other parameters as part of the optimization process, most critical being the power reliability. They also fail to provide flexibility to the designer, meaning that depending on what is the system constraints are, they do not have much experimentation to do with the algorithms.

Sharafi and ELMekkawy [15] provided a comprehensive analysis of the optimization techniques and cost functions used by various researchers. Most researchers tended to use single objective cost functions [12]–[16] aimed at minimizing cost or improving reliability. In the cases where multiobjective functions were used, the goals varied amongst minimizing cost, emissions or unmet load [15]. For example, Katsigiannis et al. [17] used a multiobjective cost function that minimized annualized cost and the emissions in the system, while Abedi et al. [18] used evolutionary algorithm to minimize the a multiobjective cost function comprising of the total cost, the system emissions and the power deficit. Multiobjective cost functions have the added advantage of providing increased flexibility to the designer of the system [9]. However, the multiobjective cost functions found in literature do not include the impact of having excess power generated in the system. This can lead to the system generating too much power than it actually requires.

There is a direct correlation between the power output of a RES component and the cost. However, none of the papers reviewed used this correlation in the modelling of their respective systems. This paper aims to build on the work done on multiobjective cost function development, by integrating this correlation into the system model. It does so by using both the power deficit of the system and excess power generated by the system to be an indirect determiner of the power reliability and cost of the system, and optimally minimizes this using genetic algorithm. This means the sizing technique avoids oversizing the system, which was not considered in the previous research.

2. Problem Formulation

2.1. System Schematic

Fig 1 shows the schematic diagram of the off-grid RES system. It comprises a discrete number of wind turbines and PV arrays which provide power to a group of households

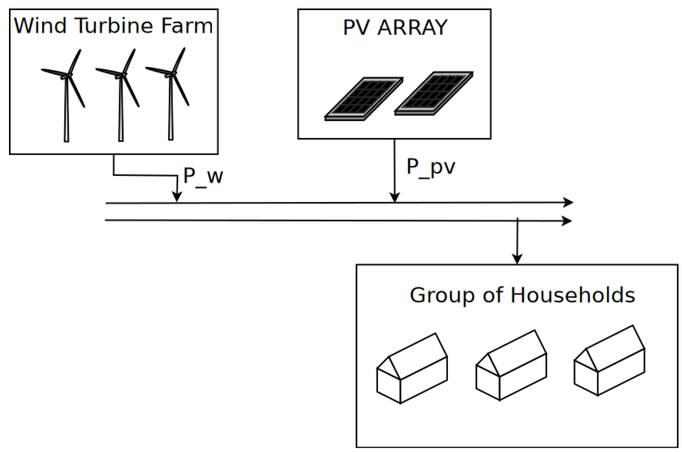


Fig. 1. RES Schematic

2.2. Solar Energy

Solar Energy refers to energy drawn from the sun. It is harvested by either heat or light conversion to electricity. The conversion of light to electricity is done using PhotoVoltaic (PV) cells, with various cell production techniques in existence like polycrystalline technology and thin film technology [19]. However, the energy output of a single cell is usually miniscule [19], so multiple cells are arranged in series and parallel to create a PhotoVoltaic (PV) array. The energy output from such an array can be modelled [12] using the Equations 1 and 2.

$$V_{pv} = V_{cell} \times N_{series} \tag{1}$$

$$P_{pv} = \frac{I_{sc} \times G \times V_{pv} \times N_{parallel}}{LF} \tag{2}$$

where V_{pv} is the output voltage of the system, V_{cell} is the output voltage of a single cell, N_{series} is the number of cells in series, P_{pv} is the output power of the PV array, I_{sc} is the short circuit current of the panel, G is the solar irradiance on the panel surface and $N_{parallel}$ is the number of parallel series cells.

2.3. Wind Energy

Wind is moving air. The electrical energy from wind is drawn through conversion of the kinetic energy of wind. As such, the wind energy is a function of velocity. Wind turbines have three main regions of operation, region 1 when the turbine is starting up, Region 2 where the turbine in in operation and it should capture as much power as possible and Region 3 where the wind speeds are so high that the turbine has to limit the power captured for safety [20]. The operational region use in this paper is Region 2. As noted in [20], the output power of wind turbine can be estimated as shown in Equation 3.

$$P_w = \begin{cases} 0 & V < V_c \\ \frac{V^k - V_c^k}{V_R^k - C_c^k} P_R & V_c \le v \le V_R \\ P_R & V_R \le v \le V_F \\ 0 & V > V_F \end{cases} \tag{3}$$

where V_c is the cut in velocity (the speed below which the wind turbine outputs no power), P_R is the rated power, V_R is the rated wind speed, V_F is the rated cut-out speed (the speed above which the wind turbine gets damaged, so a braking mechanism is used to bring the rotor to a standstill, hence no power is output) and k is the Weibull shape factor.

2.4. Optimization Problem

The optimization parameters considered during sizing in this research are:

1) Minimizing downtime of the system (Power Reliability)
2) Minimizing the total cost of the system

To determine the downtime, the parameter defined as Loss of Power Supply Probability (LPSP) is used as defined by Nafeh et al. [14]. This parameter provides a long term average fraction of the required power that is not supplied by the system (power deficit). It is defined as show in Equation 4.

$$LPSP = \frac{\sum_{t=1}^{T} LPS(t)}{\sum_{t=1}^{T} E_l(t)} \tag{4}$$

where $LPS(t)$ is the amount of power required that could not be supplied by the system for hour t and $E_l(t)$ is the load demand for hour t.

It is observed that the more expensive products generally have better efficiency and produce more power. This means that the more power the system provides, the higher the cost of the system. Therefore, a parameter known as Excess of Power Supply Probability (EPSP) is defined, which provides the long term average of the excess power that goes to waste. It is defined as shown in Equation 5.

$$EPSP = \frac{\sum_{t=1}^{T} EPS(t)}{\sum_{t=1}^{T} E_l(t)} \tag{5}$$

where $EPS(t)$ is the extra power supplied by the system at hour t.

Therefore, the problem becomes a multiobjective one that aims to reduce the function shown in Equation 6

$$C_{el} = \min\{w_1 LPSP + (1 - w_1) EPSP\} \tag{6}$$

where w_1 determines the amount of weight given to each objective.

The flow chart, shown in Fig 2 demonstrates how the cost function for a particular PV array and wind turbine are obtained. This is the cost that is used in the GA to determine fittest components of a population.

2.4.1. Constraints

The constraints used in this study are shown in Equations 7 and 8

$$0 \le N_{pv} \le N_{pv_{\max}} \tag{7}$$
$$0 \le N_{wt} \le N_{wt_{\max}} \tag{8}$$

where N_{pv} is the number of solar panels in consideration, N_{wt} is the number of wind turbines in consideration, $N_{pv_{\max}}$ is the maximum number of solar panels which can fit into the allocated area as shown in Equation 9 and $N_{wt_{\max}}$ is the maximum numer of wind turbines which can fit into the allocated area as shown in equation 10

$$N_{pv_{\max}} = \frac{A_{pv_{\max}}}{A_{pv}} \tag{9}$$
$$N_{wt_{\max}} = \frac{A_{wt_{\max}}}{A_{wt}} \tag{10}$$

where $A_{pv_{\max}}$ is the maximum area allocated for the solar system, $A_{wt_{\max}}$ is the maximum area allocated from the wind turbines, A_{pv} is the area occupied by a single PV array and A_{wt} is the area occupied by a single wind turbine.

2.5. Expense Calculations

There is a need to determine the actual cost of a system determined after optimization. This is so as to provide a benchmark on which to compare results between various cost functions applied to the problem. The total expense of setting up and maintaining a Renewable Energy System should include the acquisition cost, replacement costs of the components, operation and maintenance costs and the salvage value [21]. These are all dependent on the expected lifespan of the project.

The acquisition cost is shown in Equation 11.

$$A = I_k k \tag{11}$$

where I_k is the individual cost of a component and k is the number of components in consideration.

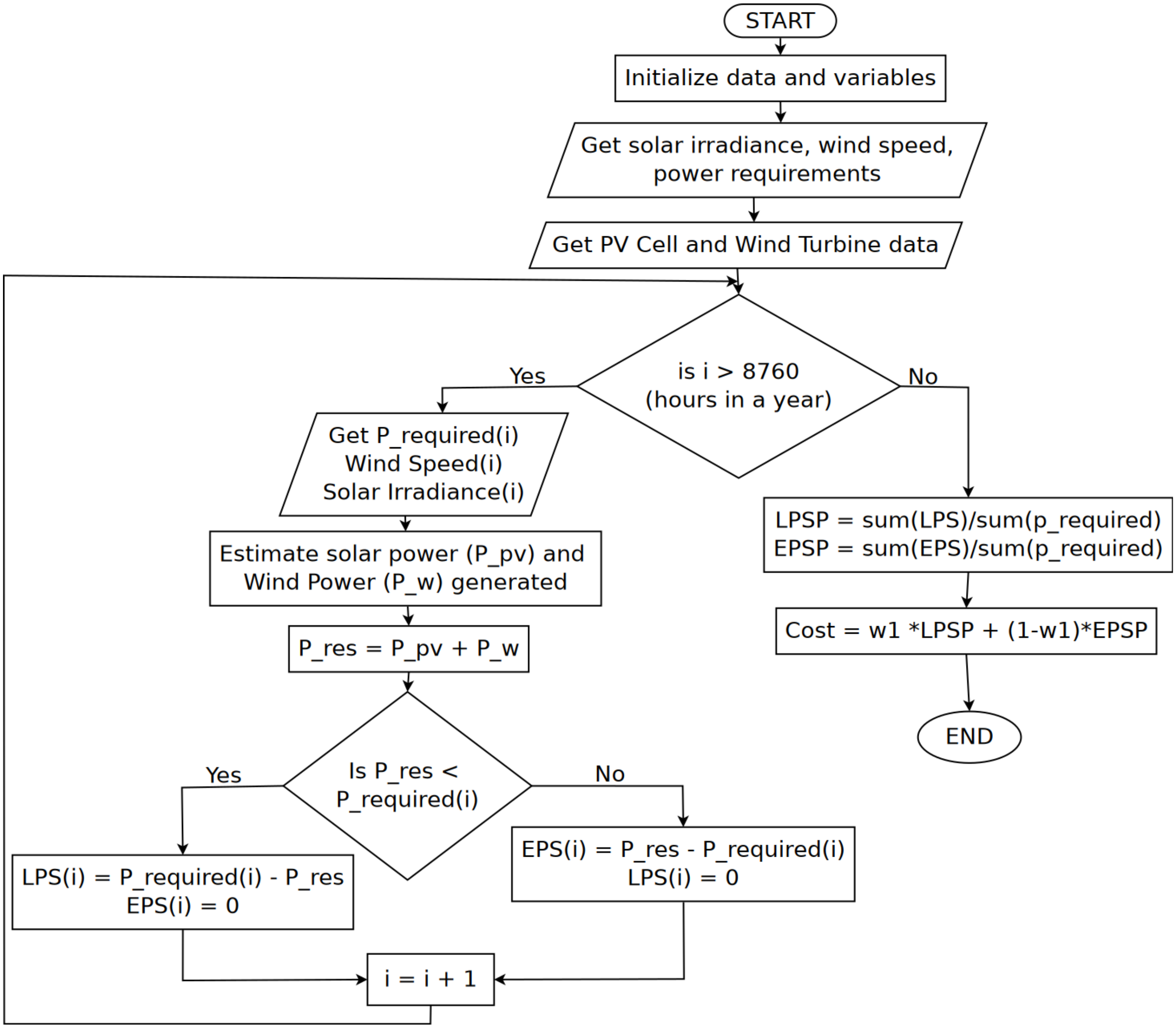


Fig. 2. Flowchart showing simulation of a particular PV array and wind turbine

Replacement costs refer to the number of times a component needs to be replaced. This number is shown in Equation 12.

$$X_r = \frac{N}{L} - 1 \tag{12}$$

where N the expected lifetime of the project and L the expected lifetime of the components.

The replacement costs therefore are show in Equation 13.

$$R = I_k N X_r \tag{13}$$

For operation and maintenance costs, the unit cost per component is multiplied by the number of components and the expected lifetime of the project as shown in Equation 14.

$$OM = \phi k N \tag{14}$$

where ϕ is the operation and maintanance costs of a single component for 1 year.

Inflation and salvage value of the components are not considered when factoring in the cost of the components in this study.

3. Genetic Algorithm

Genetic Algorithm (GA) is a heuristic optimization technique that is inspired by Darwinian evolution [22]. It was originally conceptualized by J. H. Holland [23], and operates on a set of artificial chromosomes which evolve over time until the best solution is found. GA is chosen as the optimization algorithm because the problem variables can be easily included in the GA chromosome without any further modifications. Furthermore, it is the heuristic algorithm used by the baseline, so this provides a valid baseline for comparison.

The GA chromosome in use is a vector containing four parameters.

$$chro = [I_{pv}, N_{pv}, I_{wt}, N_{wt}] \tag{15}$$

where I_{pv} refers to the index of the PV component in consideration, N_{pv} refers to the number of PV cells, I_{wt} referse to the index of the wind turbine in consideration and N_{wt} is the number of wind turbines.

To get the fitness of a unit chromosome, the chromosome is fed into a function which picks out the appropriate solar panel type and wind turbine type from a matrix of components using I_{pv} and I_{wt}. The solar panel type and wind turbine type is an array containing parameters that can be used to calculate P_{pv} and P_{wt} as shown in Equations 2 and 3. These powers from unit components are combined using the N_{pv} and N_{wt} from the chromosome with the Equation 16 to provide the total power that can be supplied by the renewable energy sources.

$$P_{res} = P_{pv}N_{pv} + P_{wt}N_{wt} \tag{16}$$

The GA algorithm has to be initialised with some constant set of parameters in order to provide a level starting point from which different cost functions can be compared. The GA parameters used for this include:

The $CrossoverFrac$ which specifies the fraction of the upcoming generation which will be producted by crossover, apart from the best children. This is set to 0.5.

The $PopulationSize$ which determines how many individuals exist in each generation. This is set to 50.

The $StallGen$ which determines the generation when the algorithm stops if the average relative change of the best fitness is less than or equation to function tolerance. This is set to 125.

The $Generations$ which determines the maximum number of iterations the GA will perform. This is set to 150.

4. General Data

4.1. Meteorological Data

The region in consideration is found in Juja, Kenya. The latitude is 37.01 and longitude is -1.09. The weather data is sourced from NASA [24], but provides only monthly averages of both wind and solar irradiation. The Collares-Pereira and Rabl method [25] is used to convert the monthly averages into hourly solar irradiation using the software IHOGA [26]. The wind speed is also converted into hourly values over a period of one year using IHOGA.

Solar irradiation for a typical year is shown in Figure 3 whereas Figure 4 shows the wind speed for a typical year.

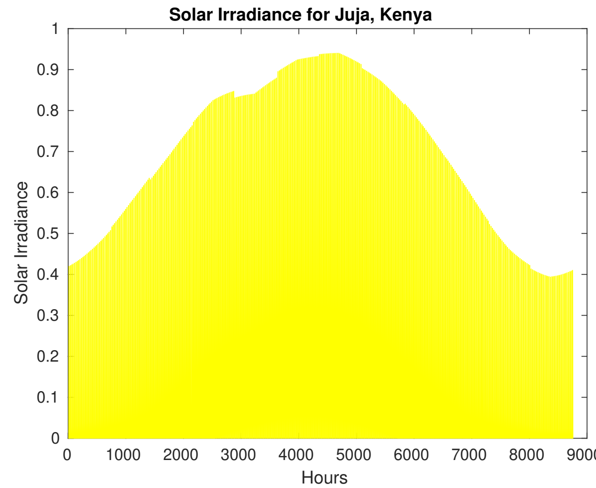


Fig. 3. Yearly Solar Irradiance for Juja, Kenya

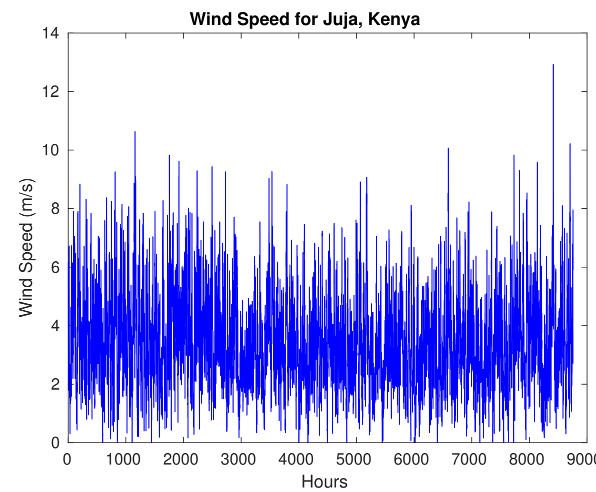


Fig. 4. Yearly Wind Speed for Juja, Kenya

It is assumed that the solar irradiance and wind speed are constant during the hour in consideration.

4.2. Load Data

Various households in Kenya have varying demands. Based on research by Magambo [27], three load profiles were used. Furthermore, the system is taken to supply multiple households, with a group of 20 used in this research. Therefore, for the design problem, each load profile was multiplied by 20 to get the approximate load for a group of households.

The first load profile considered was that of a household that does not consume a lot of electricity. This is considered as the minimal household and has a consumption $\leq 3.63kWh$. This profile is shown in Fig. 5a.

The second load profile is that of a household that consumes nominal electricity. This is considered to be the nominal household and has a consumption of $9.55kWh$. The profile is shown in Fig. 5b.

The last load was that of a household considered to consume a significant amount of electricity in Kenya. This is considered as the high household and has a consumption $\geq 17kWh$. This profile is shown in Fig. 5c.

4.3. Baseline

Nafeh's [14] work is used to form the baseline. It was used to optimize the cost of a household in a residential remote area near Hyrghada city of Egypt in the original work. This is used to compare the results of the new model developed against his model. The cost function used in Nafeh's work is shown in Equation 17

$$C_T = min \sum_{k=1}^{K} (I_k + R_k + OM_k) \quad (17)$$

under the constraints shown in Equation 18.

$$0 \leq LPSP \leq LPSP_{max} \quad (18)$$

where I_k is the initial investment, R_k the replacement cost, OM_K the operations and maintenance cost, $LPSP$ is the Loss of Power Supply Probability and $LPSP_{max}$ is the maximum allowable $LPSP$ taken to be 0.2 in this study.

Both the baseline and novel model are used with GA to observe the performance of both models. The performance is analyzed on the basis of the cost and the power reliability.

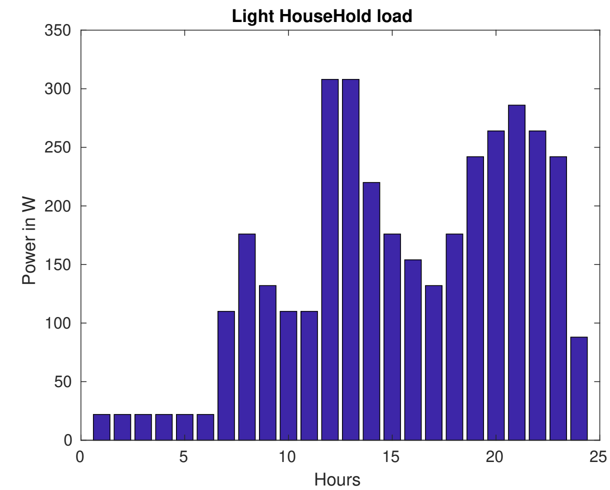
4.4. Components in Consideration

4.4.1. Wind Components

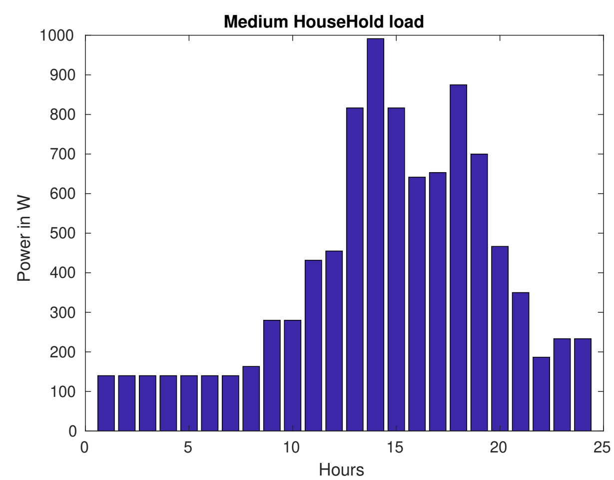
The list of wind turbines considered during the optimization problem are shown in Table 1, where $Cost$ is the cost of the wind turbine in \$ (US dollars), OM is the yearly Operational and Maintenance cost of the wind turbine in \$ (US dollars), $Life$ is the expected life span of the wind turbine in $years$, V_c is the cut in velocity in m/s, P_r is the rated power in W and V_F is the rated cut-out speed in m/s.

Table 1. Wind Turbines considered in the sizing problem [26]

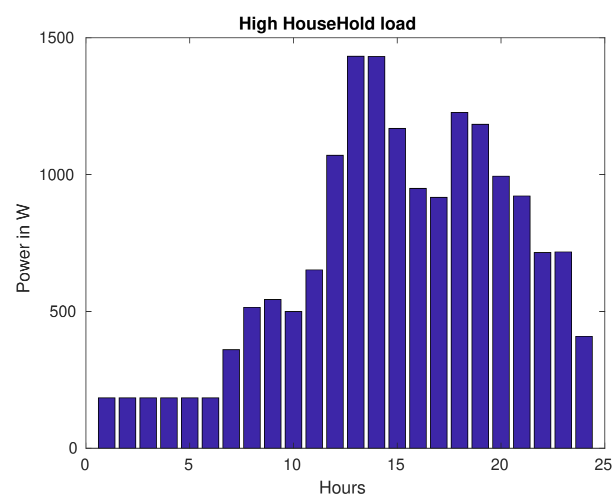
Name	Cost	OM	Life	P_r	V_c	V_F
SW: Air X	1228.50	65.00	10	400	3.1	49
SW: Whisper100	3724.50	110.50	15	900	3.4	55
SW: Whisper500	12610.00	253.50	15	3000	3.4	55
Bornay: 600	5531.50	110.50	15	600	3.5	60
Bornay: 1500	6337.50	127.40	15	1500	3.5	60
Bornay: 3000	9821.50	196.30	15	3000	3.5	60
Bornay: 6000	15672.80	291.20	15	6000	3.5	60
Hummer: HWP-10	18200.00	364.00	20	10000	2.0	50
Hummer: HWP-20	28600.00	572.00	20	20000	2.0	50
Hummer: HWP-30	44200.00	884.00	20	30000	2.0	50



(a) Household with low power requirements



(b) Household with medium power requirements



(c) Household with high power requirements

Fig. 5. Household power requirements

4.4.2. PV Components

The PV components considered in this research are shown in Table 2, where $Cost$ is the amount of money required to get one PV in \$ (US dollars), $O\&M$ is the yearly operational and maintenance costs in \$ (US dollars), $Life$ is the expected lifespan in years, I_{sc} is the short circuit current of the panel in $Amperes$ and V is the output voltage of a single array in $Volts$.

Table 2. PhotoVoltaics considered in the sizing problem [26]

Name	V	Isc	Cost	O&M	Life
aSi12-Schott: ASI100	12	6.79	143	1.43	25
SiM12-Atersa: A10J	12	0.68	58.5	0.585	25
SiM12-Atersa: A20J	12	1.32	98.8	0.988	25
SiP12-Atersa: A66P	12	4.06	195	1.95	25
SiP12-Atersa: A95P	12	5.51	224.9	2.249	25
SiP12-Atersa: A135P	12	8.23	249.6	2.496	25

5. Results

5.1. Optimization

The baseline for a single run of the GA is shown in Figure 6.

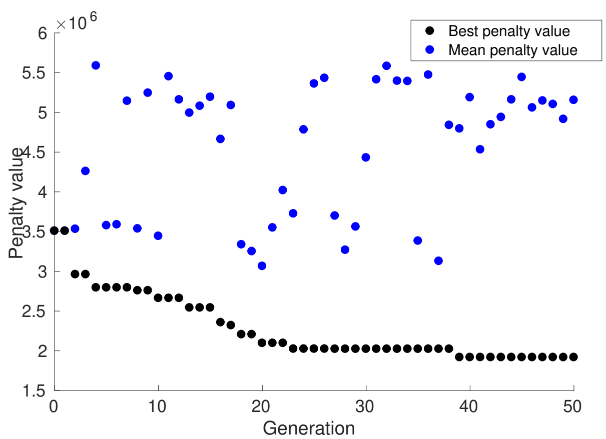


Fig. 6. Baseline objective function single run

The multi-objective function's results are shown in Figure 7.

The blue dots in the figures show the mean fitness of a particular generation. The black dots show the best item in a particular generation. As can be seen in both, the black dots tend to have a lower fitness function over time, meaning that the optimization is getting better and better. Also it can be noticed that the optimization of the multiobjective function takes less generations to arrive to an optimum solution.

Due to the heuristic nature of GA, each cost function was run 100 times, and the average performance obtained and compared as shown in Table 3. For the multiobjective function, the value of w_1 chosen was 0.2, meaning it offered more weight to the cost (the weight of $EPSP$ is 0.8) than the reliability of power($LPSP$). Therefore, as can be observed, the cost is better than the baseline whereas its power reliability performs worse than the baseline.

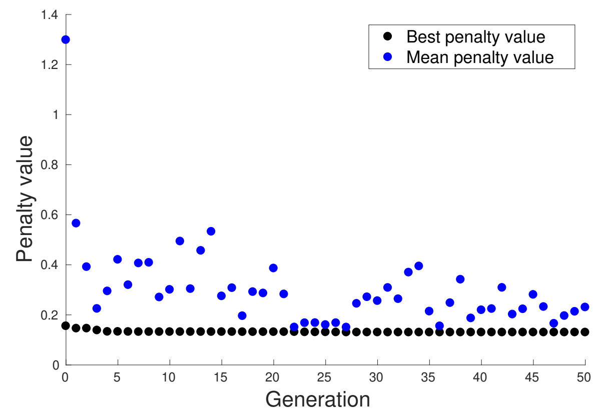


Fig. 7. Multiobjective function single run

Table 3. Averaged results from baseline and novel cost function

	Cost Function	Cost($)	LPSP
Small Household	Baseline	217661.80	0.0000
	EPSP-LPSP	39465.80	0.0694
Nominal Household	Baseline	341516.94	0.0000
	EPSP-LPSP	153988.25	0.0154
Large Household	Baseline	1854843.83	0.0000
	EPSP-LPSP	264382.98	0.0178

Table 4 shows the most efficient components chosen during the run by each cost function. The column N_{pv} refers to the number of solar panels selected and N_{wt} refers to the number of wind turbines selected. As the load increases, more powerful components are selected and the number of components also tends to increase. These are the optimal results provided by the novel cost optimization problem.

Table 4. Optimal chromosomes for each cost function

	Small Household	
	Baseline	EPSP-LPSP
PV	SiP12-Atersa: A135P	aSi12-Schott: ASI100
N_{pv}	146	60
Wind Turbine	Hummer: HWP-10	Bornay: 1599
N_{wt}	7	1
	Medium Household	
	Baseline	EPSP-LPSP
PV	aSi12-Schott: ASI100	SiP12:Atersa
N_{pv}	178	298
Wind Turbine	Hummer: HWP-10	Southwest: Air X
N_{wt}	22	43
	Large Household	
	Baseline	EPSP-LPSP
PV	aSi12-Schott: ASI100	SiP12-Atersa: A135P
N_{pv}	200	200
Wind Turbine	Bornay: 6000	Bornay: 1500
N_{wt}	55	12

The components showed in Table 4 shows the optimal solutions for the problem. The components chosen between the novel and the baseline cost functions are observed to be different both in the type of component and the quantity selected.

On average, it was observed that the cost of the multi-objective function were 18.97% less than those achieved by the baseline. The power reliability was however worse than the baseline by an average of 7.83%. However, this could be solved by changing the weight used. For example, if a weight of 0.5 is used, it is found that the multiobjective function is 14.97% less costly than the baseline, whereas power reliability becomes better than the previous weight, at 3.83% worse than the baseline.

5.2. Effect of weight w_1 on Selection

Varying the weight w_1 used in the novel cost function results in different choices made during optimization. This is shown in Table 5. Increasing the weight w_1 results in an increase in $EPSP$, which means that the amount of power the system generates that is not put to use (power wasted) also increases. The $LPSP$ value also decreases which means that the power deficit of the system also goes down with an increase in w_1.

Table 5. Effects of varying weight on cost and performance

w1	Small Household		Nominal Household		Large Household	
	Cost	LPSP	Cost	LPSP	Cost	LPSP
0.0	1797.69	0.1430	44906.11	0.2270	22140.30	0.2439
0.1	19357.42	0.0000	54745.60	0.0210	102138.40	0.0230
0.2	22894.30	0.0000	85679.26	0.0084	127998.00	0.0090
0.3	22173.32	0.0258	95673.50	0.0052	160322.50	0.0015
0.4	42634.80	0.0109	108603.30	0.0021	192647.00	0.0000
0.5	42497.94	0.0040	121533.10	0.0009	231436.40	0.0000
0.6	59894.90	0.0236	140927.80	0.0002	276690.70	0.0000
0.7	66197.30	0.0225	146203.20	0.0078	273915.20	0.0049
0.8	86100.30	0.0099	194095.20	0.0021	369699.20	0.0003
0.9	109063.14	0.0003	289879.20	0.0000	577231.20	0.0000
1.0	1646819.20	0.0000	1646819.20	0.0000	1646819.20	0.0000

Table 6. Effects of varying weight on EPSP and LPSP

w1	Small Household		Nominal Household		Large Household	
	EPSP	LPSP	EPSP	LPSP	EPSP	LPSP
0.0	1.7155	0.1430	2.4885	0.2270	2.1818	0.2439
0.1	3.2142	0.0974	3.9049	0.1120	4.9864	0.1681
0.2	4.5885	0.0694	5.6542	0.0154	6.0890	0.0178
0.3	4.9129	0.0402	7.0426	0.0084	6.5964	0.0115
0.4	5.2451	0.0236	7.0755	0.0078	7.2133	0.0089
0.5	6.3878	0.0218	7.9841	0.0075	7.4325	0.0049
0.6	9.1408	0.0183	8.4958	0.0052	7.5670	0.0024
0.7	11.9287	0.0177	9.7779	0.0044	8.1458	0.0015
0.8	12.2214	0.0134	10.2702	0.0021	10.6312	0.0003
0.9	13.2243	0.0099	14.9667	0.0000	12.7528	0.0000
1.0	18.9571	0.0000	68.2259	0.0000	40.1454	0.0000

The $EPSP$ parameter has a direct correlation to cost of the system while the $LPSP$ parameter has a direct correlation to power reliability. As such, the table 5 can be used to provide a reference of the cost to power reliability options a designer has. As can be observed, when w_1 increases from 0 to 1, the power reliability improves (i.e. gets closer to 0), while the amount of excess power increases. Both parameters experience inverse behaviour, so the increasing w_1 will improve one while making the other worse and vice versa.

6. Conclusion

Cost and reliability of a RES system are huge factors to consider before committing to build one. However, this is a balancing act that requires careful design. Current methods do not offer this flexibility for consideration. A multiobjective cost function with the potentional to save on both energy costs and power reliability has been developed. However, this also depends on the weight provided by the designer. It is possible, given the system constraints like budget and power efficiecy, to choose the best weights for a system given the trend shown where as weight increases the total system cost increases while power reliability improves. A sample usecase has been provided that compares the new cost function (with a preselected weight) and a baseline implementation, and it is discovered that the new implementation provides better cost than the baseline but at the cost of losing power reliability. However, given the flexibility of the new implementation, this can be solved but at a higher cost. A table providing the effect of weight on the parameters has also been developed with this in mind. This should provide a reference for which weight to choose, helping the designer along the way.

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