Universal Access to Electricity: Grid versus Decentralized Solutions in Ghana

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Abstract:

This paper aims to contribute to the literature on mass electrification by investigating the comparative performances of three mass electrification algorithms. The first two are the algorithms by (Parshall et al., 2009) and (Deichmann et al., 2011). Whilst these are cited in the literature a comparative analysis of their performances had not been conducted. This paper introduces a third algorithm known as the multiobjective genetic algorithm for partial grid electrification (MOGA-PGE). All three algorithms are designed to minimise the total costs of universal electrification through optimal allocation of electrification sources among un-electrified settlements in countries with low pre-existing electricity infrastructure. The paper considers a case study of Ghana and subjects the algorithms to three electrification sources namely the centralised Ghanaian grid network, standalone solar photovoltaics (PVs) and standalone wind turbines. In simulating these algorithms, this paper explicitly accounts for the existing electricity infrastructure in the country. Sensitivity analysis on the existing reference algorithms shows that they have varying sensitivities to the cost factors of electrification. The result also shows that all three algorithms have varying outcomes for the total costs of universal electrification and the composition of electrification sources. It also shows that the algorithms are practical in the sense that a priori expectations of an ideal mass electrification outcome were realised for all three.

Keywords: cost minimisation, mass electrification, algorithms, comparative analysis, grid, renewable energy

1. Introduction

According to the International Energy Agency (IEA, 2010), over 1.6 billion of the world's population mostly living in rural regions of developing countries have no access to electricity. The literature suggests that lack of access to affordable and reliable electricity is a major determinant of poverty in these regions. Access to electricity has been shown to have significant health benefits for rural households as it is essential for domestic usage such as lighting and cooking and for powering equipment in medical facilities. A study by the Independent Energy Group (2008) showed that indoor lighting and cooking that is typical of un-electrified rural communities increases the risk of early death by a factor of five. An Energy Management Assistance Program (2003) study also shows that students in electrified homes have higher education levels than their counterparts in un-electrified homes because electricity allows the former to study for longer periods, get higher grades and as a result stay longer in school. This leads to opportunities for upward mobility in society hence poverty reduction. At a national level, opportunities for economic activity resulting from access to electricity may contribute significantly to poverty reduction.

In many Sub Saharan Africa (SSA) countries, urban populations remain underserved by inefficient and unreliable centralised national grids whilst fewer than 10% of rural communities have any access to electricity at all (Parshall et al. 2009). For electricity planners in these countries, extensions of the centralised grid to only a subset of un-electrified settlements is the realistically attainable paths to further centralised grid electrification in the short to medium term. Constraints confronting planners may be technical (i.e. insufficient grid generation capacity, ageing and failing transmission and distribution infrastructure, geographic barriers to grid extensions, etc); and considerations may be economic (i.e. the economics of supply for sparsely populated and remotely located settlements, unwillingness to pay for electricity due to poverty, etc) and/or socio-political (i.e. political targeting of mass electrification as policy tool for poverty reduction), etc. Meanwhile the potential for decentralised systems such as solar, wind, hydro, geothermal, biofuels, diesel generators, etc for rural communities in these countries is enormous. In Namibia for example, annual potential production from renewable energy sources is about a hundred times the current energy consumption under realistic assumptions of technical feasibility (Deichmann et al. 2011). Other SSA countries such as Senegal, Sierra Leone and Benin have annual renewable generation potential of about 10-12 times their current electricity consumption. Further, the costs of renewable energy technologies are forecasted to decrease over time due to technological advancements in their development.

In designing least cost strategies for increasing access to electricity in these countries key questions include what the balance should be between the extensions of the electricity grid versus the use of stand-alone technologies, and for those locations where grid extension is considered best what is the least cost way of extending the grid to these communities?

There have been a large number of mathematical programming studies addressing different aspects of the problem of electrification. Many of these methods are focused on the gridded network aspects of electrification and employ mathematical programming techniques such as mixed-integer-programming (Adams et al 1974; Gonen et al 1981; Hongwei et al. 1993; Bouchard et al. 1995; Lin, Chin 1998; Ramirez-Rosado et al. 1999; Kocaman et al. 2012). Despite their theoretical attractiveness, the complexity and multi-layered nature of the problem combined with the fact that planners are likely to make decisions on extending in a sequential manner have limited the usefulness of programming approaches which aim to find a global optimal solution.

An alternative approach which has been extensively employed has been to employ heuristic methods based on sensible sequential rules to find ‘good’ solutions (Deichmann et al. 2011; Parshall et al. 2009; Zvoleff et al. 2009; Kaijuka, 2007). They do not require network planners to solve complex mathematical programming problems, although the heuristic may employ simple optimization methods for elements of the solution. In theory they also lend themselves more naturally to reality of incremental extension of the network. By definition, being ad hoc there is no measure of the degree to which these heuristic approaches approach optimality. Planners also have often multiple objectives and neither the programming nor the heuristic approach has typically taken these into account. Genetic Algorithms provide a potential alternative method where multi-objectives may be taken into account while searching for a global optimum. These methods have been used to determine the partitioning of a electricity grid into power districts (Bergey et al. 2003).

While a range of different approaches to the appropriate balance between grid and standalone renewables and the optimal extension of the electricity network have been undertaken, there has no analysis of comparative performance of these applied to real world problem. The aim of this paper is to consider the relative performance of the heuristics used by Deichmann et al. (2011) (the DA algorithm) and by Parshall et al. 2009 (the PA algorithm), with a Multi-Objective Genetic Algorithm (the MOGA-PGE algorithm) in finding the best balance between network extension and standalone renewables (solar and wind) in Ghana in terms of levelised costs.

Previous studies have noted the influence of the geography of a country on the outcomes (Zvoleff et al. 2009), and it is likely that that performance of the algorithms will also be affected by the country's geography and the nature of the problem formulation. Therefore to ensure the problem formulation is as close to the one faced by Ghanaian planners as possible, we take the existing Ghanaian network as the starting point rather than assuming that no network exists (Deichmann et al., 2011).

The rest of the paper is organised as follows. Section 2 discusses the three different approaches to consider the grid expansion versus standalone renewables. Section 3 discusses the Geographic Information Systems (GIS) data and other Ghanaian data sources and transformations used in the analysis. Section 4 discusses the results and Section 5 briefly concludes.

2. Heuristic versus GA Algorithms

2.1 The DA Algorithm.

Deichmann et al. (2011) studied the feasibility of decentralised energy services in SSA with emphasis on Ethiopia, Ghana and Kenya. In doing so they developed a spatially explicit algorithm that 'estimates the comparative costs of network and decentralised electricity provision' (Deichmann et al. 2011) across countries with low pre-existing electricity network coverage. The algorithm determines settlements within a country where alternative electricity generation sources are competitive relative to grid electricity. The DA algorithm essentially seeks to solve the network feeder routing optimisation problem, the objective function of which is to minimise the total length of transmission and distribution line connections in the electricity network. It adopts Prim's (1957) variation of the Minimum Spanning Tree (MST) algorithm that is used extensively in routing optimisation. At each step of the MST algorithm, the shortest segment emanating from the set of settlements already present in the network to the set of un-electrified settlements is selected. Segments that would create a loop are avoided. In the MST variation being adopted by the DA algorithm, least inter-nodal connection lengths are minimised.

The DA algorithm begins with a setup of ***n*** un-electrified demand settlements and ***k*** power generation plants or bulk supply points (BSP). The algorithm works under the assumption that there are more demand settlements in the network than there are BSPs. The algorithm sets out by assigning the (k+1)th BSP of the network to the un-electrified demand settlement with the highest aggregate electricity demand in the network. The BSP assigned settlement is connected to the nearest existing generation plant or BSP settlement with a high voltage (HV) transmission line, thus forming part of the set of BSP settlements in the extended transmission network. All the un-electrified demand settlements within the technically feasible threshold distance of 120km of this BSP settlement are then connected to the BSP settlement using medium voltage (MV) distribution lines. The MV connection from the assigned BSP settlement to the settlements identified within its threshold is done via Prim's (1957) MST algorithm. The BSP settlement and all the connected demand settlements to it form a distinct geographic zone in the algorithm. Household to household connections in the individual settlements of the geographic zone are made via low voltage (LV) distribution line routing.

In subsequent steps, the DA algorithm repeats the above procedure; it assigns a BSP to the next largest demand settlement, connects the BSP settlement via HV wiring to the nearest generation plant/BSP settlement in the transmission network, determines the remaining un-electrified demand settlements within the threshold distance of the assigned BSP settlement and then connects them via MV wiring using Prim's MST algorithm. This procedure is repeated until all of the un-electrified demand settlements within the subject country are within a BSP/geographic zone. The algorithm then terminates.

Each sequential step of the DA algorithm represents an investment stage. After defining the geographic horizon for that stage and calculating its levelised cost of grid electricity, it also calculates the levelised cost of investments in alternative generation sources of electricity for the same geographic zone. Alternative generation sources in this study include only standalone 500W solar PVs and 450W wind turbine systems. Finally the DA algorithm when terminated shows the levelised costs of all technologies for all the geographic zones. All geographic zones are served with their least levelised cost technology.

2.2 The PA Algorithm.

Parshall et al. (2009) developed a spatial electricity planning algorithm 'to guide grid expansion in countries with low pre-existing electricity coverage'. The PA algorithm is similar to the DA algorithm in its objective which is to minimise the total cost of universal electrification; and its consideration of alternative generation sources to identify the extent of grid extension. Like the DA algorithm, the PA algorithm is sensitive to electricity demand and the geographic characteristics of the subject country. Parshall et al. (2009) modelled Kenya in their study.

The PA algorithm begins by computing the internal grid levelised cost for all the un-electrified settlements in the subject country individually. The internal grid levelised cost is a function of all intra-nodal investments in LV lines, MV lines, transformers and the internal cost of providing grid produced electricity in the settlement over the planning horizon. It does not include the cost of extending the MV or HV backbone of the national grid to the settlement. Each settlement is evaluated individually and internally. The algorithm also calculates the levelised cost of the decentralised alternative generation sources being considered i.e. standalone PVs and standalone wind turbines for all the un-electrified settlements individually.

Having determined the intra-nodal levelised costs of decentralised technologies and the intra-nodal internal grid levelised cost of the settlements, the algorithm compares the internal grid levelised cost of each settlement with the levelised costs of the decentralised technologies under considerations. If the internal grid levelised cost for an un-electrified settlement is greater than the levelised cost of at least one of the decentralised technologies being considered, the settlement is marked to be 'ineligible' for grid connection. Such a settlement is served with the least cost decentralised technology being considered i.e. either standalone PVs or standalone wind turbines, whichever has the lowest levelised cost. If the internal grid levelised cost for an un-electrified settlement is less than the levelised cost of all decentralised technologies being considered for the settlement, the settlement is identified to be 'eligible' for grid connection and is assigned metric called MV_{max}. The MV_{max} metric for an eligible settlement is defined as the maximum allowable MV extension length from the national grid to the settlement such that the total levelised cost (i.e. internal levelised cost plus levelised cost from MV extension) for the settlement is less than or equal to the levelised cost of the least cost decentralised option for the settlement.

At each iteration of the algorithm, one eligible un-electrified settlement is connected to the national grid. The connected settlement is served with an MV extension that is less than or equal to its MVmax. These connections are based on Prim's (1957) MST algorithm. The algorithm terminates when all or at least one of the following conditions are reached; i) all eligible un-electrified settlements have been connected to the network; ii) the MV_{max} of all remaining eligible un-electrified settlements is greater than the MV backbone length needed to connect the settlements to the national grid.

The determination of levelised costs of grid and decentralised alternative generation sources for the individual settlements in the PA algorithm is similar to the procedure outlined for costing in the DA algorithm with the only difference being that the PA algorithm determines these costs for individual settlements unlike the DA algorithm's determination of these costs for geographic zones. Another important difference is that unlike the DA algorithm where the HV transmission is considered and levelised costs for grid and alternative generation sources are determined sequentially at each stage, HV transmission is not considered in the PA algorithm and levelised costs in the PA are entirely determined in the first step of the algorithm for individual settlements.

2.3 Multi-objective Genetic Algorithm (MOGA-PGE)

The MOGA-PGE algorithm executes in two phases[1]. Phase-I involves, given a total of m un-electrified settlements in a country, the optimal selection of a subset of n un-electrified settlements $(n < m)$ for electrification via the extension of the existing national grid. Optimality in the selection of these settlements is in respect of three objectives found to be the most important cost factors by Nguyen (2007). These are maximising the population in the selected settlements, minimising the average distance of the selected settlements from the existing national grid and maximising the degree of clustering in the selection.[2] Phase-I is designed as a multiobjective combinatorial optimisation procedure and is achieved in the MOGA-PGE via multiobjective GA optimisation. Phase-II of the MOGA-PGE involves two processes. Firstly, the optimal least cost networking of the n selected settlements from Phase-I to the existing national grid using MV distribution lines for inter-settlement connections and LV lines for intra-settlement connections. These are achieved via Prim's (1957) minimum spanning tree algorithm (MST). Second is the optimal allocation of decentralised technologies for the remaining $m - n$ un-electrified settlements. This is achieved by simply allocating these settlements with their least cost decentralised technologies. As in the DA and PA algorithms, we specifically consider a 500W household sized solar panel and a 450W household sized wind turbine as the stand alone alternatives to the grid. After Phase-I and Phase-II of the MOGA-PGE, the total cost of universal electrification is the cost of centralised grid electrification and decentralised grid electrification. By processing the MOGA-PGE for varying levels of n, electricity planners can generate the cost profile of universal electrification for a set of un-electrified settlements. The cost profile shows the least cost selection solution for universal electrification.

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[1] Phase I is executed in MATLAB R2012a (2012) and Phase II is executed in GAMS v.23.8 (2013).
[2] As proxy for density of a selection of settlements, we use the nearest neighbour index (NNI). This is a measure of the degree of clustering in the spatial distribution of structures.

3. Data.

Ghana has a low pre-existing electricity infrastructure with network coverage of about 70% only and it is representative of many countries in SSA. The major power generation plants in Ghana include three major hydro plants controlled by the Volta River Authority (VRA) and thermal generation plants owned by independent power producers (IPPs). There are also 28 major bulk supply points (BSP) mostly located in highly populated and dense settlements across the country (Bergey et al, 2003).. The transmission network (see Figure 1) is operated and controlled by the Ghana Grid Company (GRIDCo) which is an independent institution. According to GRIDCo (2012), Ghana's transmission grid currently comprises of about 4182km of HV transmission lines and 2915MVA of transformer capacity. The location of the generation plants, BSPs and the transmission network are incorporated in the DA, PA and MOGA-PGE algorithms.

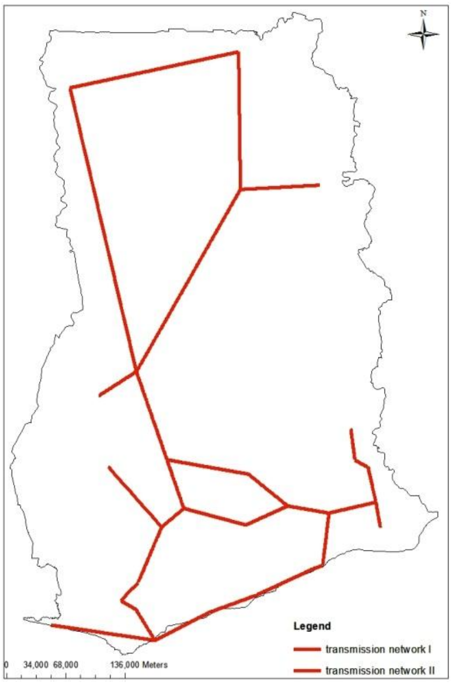

Figure 1: The transmission network in Ghana; digitised from Bergey et al (2003) and updated to include other

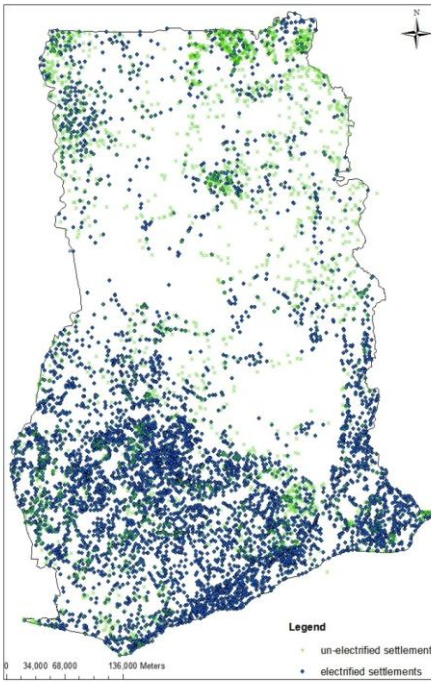

Figure 2: Distribution of electrified and un-electrified settlements in Ghana.

Data on all un-electrified communities in Ghana were sourced from the European Union Energy Initiative-Partnership Dialogue Facility (EUEI-PDF) who sponsored a survey of all un-electrified settlements in Ghana in 2010. The coordinates, populations and other demographic and economic variables for the over 2700 surveyed settlements were accounted for in the survey data. Figure 2 above shows the geographic locations of the electrified and un-electrified settlements in Ghana;

Levelised costs calculations for both grid extension uses a standard approach (Deichmann, et al. 2011) and covering MV lines, LV lines and transformers with regards their initial capital investment costs and the operations and maintenance cost over the 40 year planning period. Similarly estimates for the standalone systems include capital, operating, battery and controller costs. In order to ensure 'like-for-like' comparison of the algorithms, some of grid components covered by Parshall et al. (2011)

were not costed such as bulk supply points, static var compensators, breaker switched capacitors, etc. These are not accounted for in the simulation of the PA algorithm and were therefore not costed. We assume that there is an average of 5 people per household in all settlements and that each household demands 4kWh/day of electricity. With these assumptions, the demand for electricity at each of the un-electrified settlements can be calculated.

4. Results

4.1 DA and PA algorithms

Below, we first consider the comparative performances of the DA and PA algorithms. To provide an initial base for comparison we initially ran the two algorithms for the case where all households are provided with access to electricity via the grid. From these results the discounted cost of universal grid electrification over a 40 year period using the DA and PA algorithms are similar amounting to $8.87 billion and $8.81 billion respectively, extension involving around twelve thousand kilometres of grid extension. These estimates constitute about 20% of the country's GDP of about $40 billion in 2012 (Ghana Statistical Service, 2012), and highlight the significant and current infeasibility of providing grid access to all households.

	Base Case		**Double Household Demand**		**50% Reduction Stand-Alone Costs**	
	DA	**PA**	**DA**	**PA**	**DA**	**PA**
No. of grid settlements	524	768	2239	1350	141	535
Total MV length	2185	6509	9737	8557	671	5323
Grid costs, $ billion	1.37	2.03	7.80	4.31	0.44	1.35
No. of solar settlements	2191	1874	476	1292	2574	2107
No. of solar panel (million)	5.02	2.76	1.37	2.44	6.10	3.59
Solar panel costs, $ billion	4.93	2.51	1.34	2.22	4.70	2.50
No. of wind settlements	4	77	4	77	4	77
No. of wind turbines	682	11702	1364	23405	682	11702
Wind turbine Costs, $ million	1.28	27.70	2.56	55.40	1.03	23.40
Total costs, $ billion	6.31	4.57	9.15	6.59	5.14	3.87

Table 1: Standalone versus Grid Extension: DA and PA algorithms results

Table 1 shows the outcomes of both algorithms when wind and solar PV standalone generation sources are included as alternatives, under various assumptions. Columns 1 and 2 represent the outcomes for the base assumptions discussed in section 3. We can see from the results that the inclusion of decentralised alternative generation sources significantly reduces the total MV length of the centralised grid network for both algorithms. The reduced role of the centralised grid underscores the importance of the alternative generation sources in expanding accessibility to electricity in settings with low pre-existing electricity infrastructure. In the DA algorithm, the length of the centralised grid reduced by about 87% to accommodate over 2000 settlements for allocating solar PV units; and 4 settlements for allocating wind turbine units. Since the allocations of these technologies to settlements are based on levelised costs, the implication of the inclusion of solar and wind turbine units is that their total costs is less than the cost of the foregone grid network wiring. This yielded a 32% total reduction in the cost of universal electrification. In the PA algorithm the length of the centralised grid network reduced by about 44% to accommodate over 1800 settlements for allocating solar PV units and about 77 settlements for allocating wind turbine units. Total cost reduction as a result of the inclusion of alternative generation is about 48%.

Columns 3 and 4 provide basic sensitivity analysis when household demand doubles the base assumption. Doubling the demand for electricity increased the base scenario MV length of the centralised grid network for the DA and PA algorithms by 345% and 31% respectively whilst reducing the role of decentralised technologies in both algorithms. Overall, the DA algorithm shows a greater sensitivity to demand increases than the PA algorithm. It increased the role of the centralised grid whilst reducing the role of the decentralised alternatives by greater percentages when demand was doubled from the assumed base figure of 4kWh. Likewise it decreased the role of the centralised grid whilst increasing the role of the decentralised technologies by greater percentages when daily average household demand was halved.

Columns 5 and 6 show the impact when reduced stand-alone technology costs are halved which is important to consider given the downward trend costs over time. The result indicates that the role of the centralised grid network in the base scenario reduces significantly in both algorithms whilst the role of decentralised solar units increases significantly due to lower capital costs of decentralised units. Total electrification costs for the DA and PA algorithms reduced by 19% and 15% respectively indicating the importance of the cost of alternative generation units in mass electrification.

4.2 MOGA-PGE algorithm

As the MOGA-PGE algorithm considers multi-objectives, the nature of the results are somewhat different. The runs for Phase I of the MOGA-PGE were conducted in increments of 25 settlements for $n = 25$ to $n = 2600$ settlements (i.e. n=25, n=50, n=75, …, n=2600), where n is the prespecified number of settlements marked for grid extension at each trial. This yields a total of 104 trials. [3] Each trial results multiple Pareto solutions. By definition, all Pareto solutions are equally efficient but the total cost of electrification for choosing either Pareto solution is different. Pareto selection strategies are therefore important especially for large problems such as the one being considered in this paper. Figure 3 below is an example Pareto front with 104 solutions for $n = 1000$ in the main data;

[3] For each of these trials, the algorithm used the following exogenous GA parameters; Number of generations = 100, Crossover rate = 1.0, Mutation rate = 0.01.

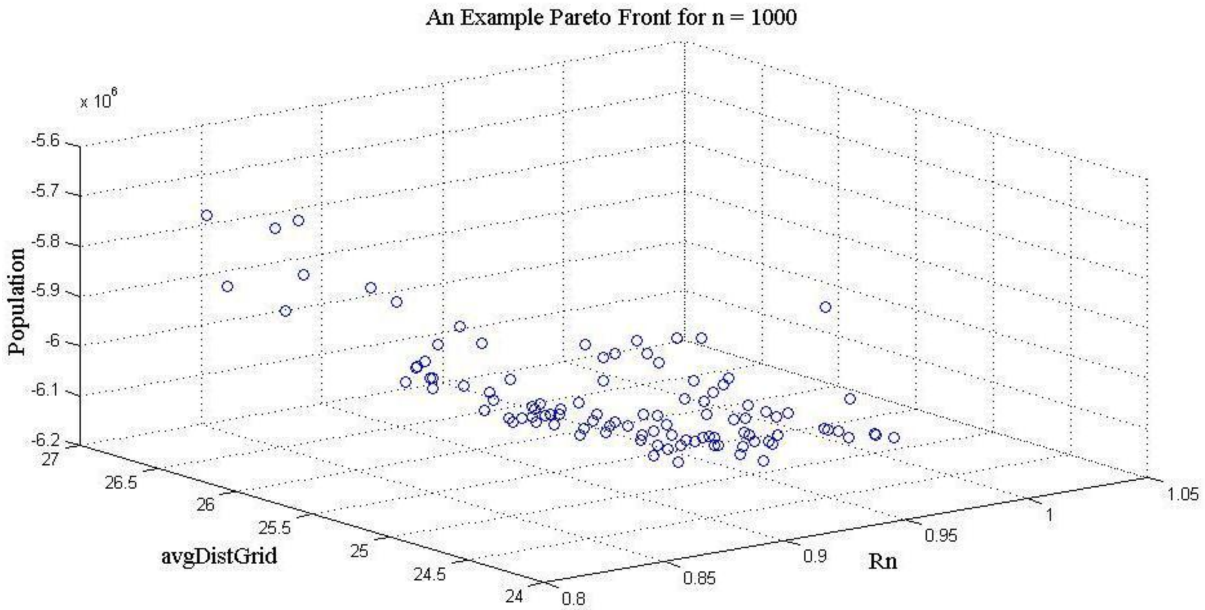

Figure 3: An example non-dominated (Pareto) front of 104 solutions for n = 1000.

Below we present the cost profiles of electrification for different Pareto selection strategies for the Ghana data and compare the performance of the MOGA-PGE with the DA and PA algorithms.

4.3 Pareto Selection Strategies.

Since there are multiple Pareto solutions for each of the 104 trials, we have opted to investigate 3 solutions for each trial. These are the extreme point Pareto solutions that are characteristic of all trials. Extreme point Pareto solutions have the property that one objective function is optimised whilst the best attainable tradeoffs in the remaining objectives are sought.

Under the first selection strategy, we choose the extreme point Pareto solution with maximum *Population* in each of the 104 trials. The cost profile of this selection strategy is as follows;

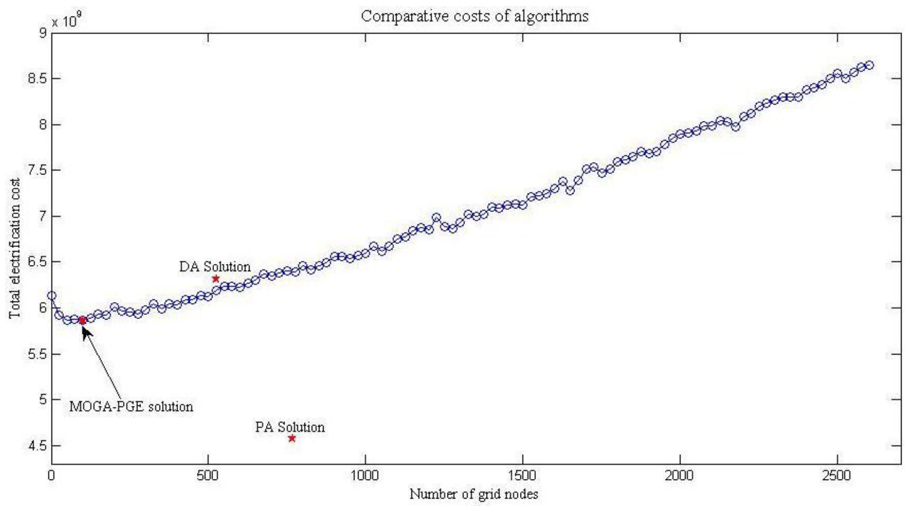

Figure 4: Cost profile for Population Pareto Selection Strategy

Figure 4 above indicates that for the current selection strategy, the least cost base scenario MOGA-PGE solution occurs for *n=100* settlements at a total electrification cost of $5.87 billion over the 40 year planning period. Interestingly, the MOGA-PGE solution compares favourably with the base scenario solution of the DA algorithm in two respects. Firstly, the optimum cost of the MOGA-PGE solution is lower than the cost of the base scenario DA algorithm solution. Secondly, for the same number of settlements to be connected to the grid as predicted by the DA algorithm (i.e. 524 settlements), the MOGA-PGE is still a cost effective solution than the DA algorithm. The base scenario PA algorithm solution however is the best cost effective solution of the three.

In the second Pareto selection strategy, we choose the extreme point Pareto solution with minimal average distance to the grid for the set of selected settlements in each of the 104 trials. The cost profile of this selection strategy is as follows;

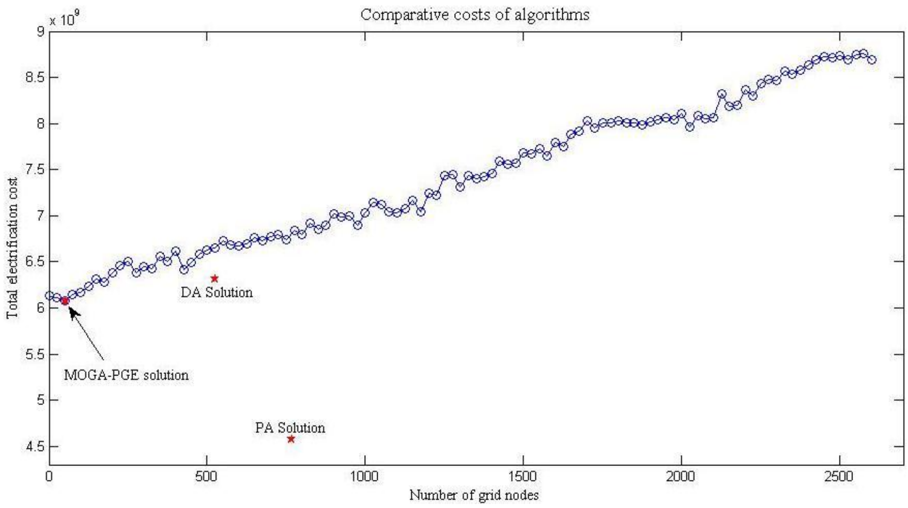

Figure 5: Cost profile for Average Distance Pareto Selection Strategy

Figure 5 above indicates that for the current selection strategy, the least cost base scenario MOGA-PGE solution occurs for *n=50* settlements at a total electrification cost of $6.08 billion over the 40 year planning period. This solution is better than that of the base scenario DA algorithm. For the same number of predicted settlements for grid electrification in the DA algorithm however, the MOGA-PGE solution is worse than the cost of the DA algorithm. It does indicate, consistent with the Nguyen (2007), that minimising the set average distance to the grid has a lower significant influence on cost relative to the population selection mechanism.

Under the final selection strategy, we choose the extreme point Pareto solution with minimal value of the nearest neighbour index, R_n for the set of selected settlements in each of the 104 trials. The cost profile of this selection strategy is as follows;

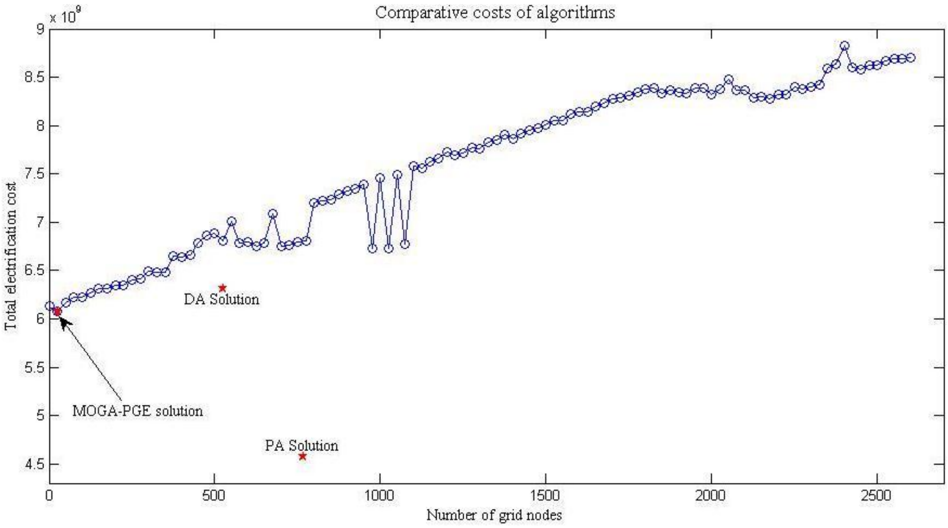

Figure 6: Cost profile for Nearest Neighbour Pareto Selection Strategy

Figure 6 above indicates that for the current selection strategy, the least cost base scenario MOGA-PGE solution occurs for *n=25* settlements at a total electrification cost of \$6.08 billion over the 40 year planning period. As in the previous cases this solution is better than that of the base scenario DA algorithm. However, for the same number of predicted settlements for grid electrification in the DA algorithm, the MOGA-PGE solution is worse than the costs of the DA algorithm. It confirms the finding of Nguyen (2007) that the number of households in a settlement (i.e. population) has a greater cost minimising influence on electrification than either of the distance of the settlement to the grid or its population density.

5. Conclusion

This paper considered the relative performance of the two heuristics used by Deichmann et al. (2011), (the DA algorithm) and by Parshall et al. (2009), (the PA algorithm), against a Multi-Objective Genetic Algorithm (the MOGA-PGE algorithm) in finding the best balance between network extension and standalone renewables (solar and wind) in Ghana. Using detailed GIS data, the three algorithms were used to consider the optimal allocation of namely the centralised grid, decentralised standalone solar PVs and decentralised standalone wind turbine units to ensure universal electrification in Ghana.

The results indicate that for grid only electrification, the PA algorithm generates outcomes which are significantly cheaper than the DA algorithm. However it does have to be noted that the DA algorithm is more robust and addresses some sub problems of electrification such as HV transmission extensions and equipment siting. Relative to the heuristic algorithms the GA approach suggests solutions which imply significantly less grid and significantly more use of stand-alone options. The implied costs associated with the GA approach were found to be lower than those associated with the DA algorithm although the nature of the relative costs depended on the Pareto selection criteria used.

REFERENCES

BERGEY, P.K., RAGSDALE, C.T. and HOSKOTE, M., 2003. A decision support system for the electrical power districting problem. *Decision Support Systems*, **36**(1), pp. 1-17.

BOUCHARD, D., SALAMA, M. and CHIKHANI, A., 1995. Optimal feeder routing and optimal substation sizing and placement using guided evolutionary simulated annealing, *Electrical and Computer Engineering, 1995. Canadian Conference on* 1995, IEEE, pp. 688-691.

CHIPPERFIELD, A. and FLEMING, P., 1995. The MATLAB genetic algorithm toolbox, *Applied Control Techniques Using MATLAB, IEE Colloquium on* 1995, IET, pp. 10/1-10/4.

DARWIN, C. and BYNUM, W.F., 2009. *The origin of species by means of natural selection: or, the preservation of favored races in the struggle for life.* AL Burt.

DEB, K., PRATAP, A., AGARWAL, S. and MEYARIVAN, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. *Evolutionary Computation, IEEE Transactions on,* **6**(2), pp. 182-197.

DEICHMANN, U., MEISNER, C., MURRAY, S. and WHEELER, D., 2011. The economics of renewable energy expansion in rural Sub-Saharan Africa. *Energy Policy*, **39**(1), pp. 215-227.

FONSECA, C.M. and FLEMING, P.J., 1993. Genetic algorithms for multiobjective optimization: Formulation, discussion and generalization, *Proceedings of the fifth international conference on genetic algorithms* 1993, San Mateo, California, pp. 416-423.

GEN, M. and CHENG, R., 1999. *Genetic algorithms and engineering optimization.* Wiley-interscience.

GOLDBERG, D.E. and HOLLAND, J.H., 1988a. Genetic algorithms and machine learning. *Machine Learning*, **3**(2), pp. 95-99.

GOLDBERG, D.E. and HOLLAND, J.H., 1988b. Genetic algorithms and machine learning. *Machine Learning*, **3**(2), pp. 95-99.

GONEN, T. and FOOTE, B., 1981. Distribution-system planning using mixed-integer programming, *IEE Proceedings C. Generation, Transmission and Distribution* 1981, pp. 70-79.

HAJELA, P. and LIN, C., 1992. Genetic search strategies in multicriterion optimal design. *Structural Optimization*, **4**(2), pp. 99-107.

HOLLAND, J.H., 1992. Adaptation in natural and artificial systems. 1975. *Ann Arbor, MI: University of Michigan Press and,* .

HONGWEI, D., YIXIN, Y., CHUNHUA, H., CHENGSHAN, W., SHAOYUN, G., JIAN, X., YI, Z. and RUI, X., 1993. Optimal planning of distribution substation locations and sizes-model and algorithm, *TENCON'93. Proceedings. Computer, Communication, Control and Power Engineering. 1993 IEEE Region 10 Conference on* 1993, IEEE, pp. 351-354.

HORN, J., NAFPLIOTIS, N. and GOLDBERG, D.E., 1994. A niched Pareto genetic algorithm for multiobjective optimization, *Evolutionary Computation, 1994. IEEE World Congress on Computational Intelligence., Proceedings of the First IEEE Conference on* 1994, IEEE, pp. 82-87.

JASZKIEWICZ, A., 2002. Genetic local search for multi-objective combinatorial optimization. *European Journal of Operational Research,* **137**(1), pp. 50-71.

KAIJUKA, E., 2007. GIS and rural electricity planning in Uganda. *Journal of Cleaner Production,* **15**(2), pp. 203-217.

KOCAMAN, A.S., HUH, W.T. and MODI, V., 2012. Initial layout of power distribution systems for rural electrification: A heuristic algorithm for multilevel network design. *Applied Energy,* .

KONAK, A., COIT, D.W. and SMITH, A.E., 2006. Multi-objective optimization using genetic algorithms: A tutorial. *Reliability Engineering & System Safety,* **91**(9), pp. 992-1007.

LIN, W.M. and CHIN, H.C., 1998. A new approach for distribution feeder reconfiguration for loss reduction and service restoration. *Power Delivery, IEEE Transactions on,* **13**(3), pp. 870-875.

LU, H. and YEN, G.G., 2003. Rank-density-based multiobjective genetic algorithm and benchmark test function study. *Evolutionary Computation, IEEE Transactions on,* **7**(4), pp. 325-343.

MURATA, T. and ISHIBUCHI, H., 1995. MOGA: Multi-objective genetic algorithms, *Evolutionary Computation, 1995., IEEE International Conference on* 1995, IEEE, pp. 289.

NGUYEN, K.Q., 2007. Alternatives to grid extension for rural electrification: Decentralized renewable energy technologies in Vietnam. *Energy Policy,* **35**(4), pp. 2579-2589.

PARSHALL, L., PILLAI, D., MOHAN, S., SANOH, A. and MODI, V., 2009. National electricity planning in settings with low pre-existing grid coverage: Development of a spatial model and case study of Kenya. *Energy Policy,* **37**(6), pp. 2395-2410.

PRIM, R.C., 1957. Shortest connection networks and some generalizations. *Bell system technical journal,* **36**(6), pp. 1389-1401.

RAMIREZ-ROSADO, I.J., DOMINGUEZ-NAVARRO, J. and YUSTA-LOYO, J., 1999. A new model for optimal electricity distribution planning based on fuzzy set techniques, *Power Engineering Society Summer Meeting, 1999. IEEE* 1999, IEEE, pp. 1048-1054.

SCHAFFER, J.D., 1985. *Some experiments in machine learning using vector evaluated genetic algorithms*.

SRINIVAS, N. and DEB, K., 1994. Muiltiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary computation,* **2**(3), pp. 221-248.

ZITZLER, E. and THIELE, L., 1999. Multiobjective evolutionary algorithms: A comparative case study and the strength pareto approach. *Evolutionary Computation, IEEE Transactions on,* **3**(4), pp. 257-271.

ZVOLEFF, A., KOCAMAN, A.S., HUH, W.T. and MODI, V., 2009. The impact of geography on energy infrastructure costs. *Energy Policy,* **37**(10), pp. 4066-4078.