SUSTAINABILITY, INCLUSIVENESS AND GOVERNANCE OF MINI-GRIDS IN AFRICA (SIGMA) RESEARCH PROJECT

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MINI-GRID PERFORMANCE ANALYSIS USING DATA ENVELOPMENT ANALYSIS

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1. INTRODUCTION TO PRODUCTIVE EFFICIENCY MEASUREMENT

Significant progress has been made in recent years towards achieving the Sustainable Development Goals, and in particular SDG7 on clean energy access. However, if the goal of universal access to energy is to be met by 2030, large-scale investment and rapid and significant action is needed. According to the IEA in 2022, approximately 733 million people still lack access to electricity globally (IEA et al, 2022). Electricity access in many low and middle-income contexts is hampered with reliability issues and supply constraints. Supplies from off-grid and mini-grid solutions are often insufficient for meeting aspirational energy access needs, and struggle to enable economic development (Ulsrud 2020, Bukari et al 2023). While frameworks such as the ESMAP Multi-tier Framework on Energy Access (ESMAP, 2015) have tried to account for variations in reliability, capacity and service quality, there remains a gap in the assessment of the performance of energy access solutions, in technical, economic and social terms. The paucity of evidence-based assessment of determinants of project or programme success has been cited by Duran and Sahinyazan (2021b). This paper seeks to apply a well-established quantitative assessment methodology known as Data Envelopment Analysis (DEA), to the energy access space, specifically in assessing the efficiencies of mini-grids in Sub-Saharan Africa. Applications of DEA methodologies to the performance analysis of distributed energy systems are limited in the literature, as are applications looking at electricity access in developing countries. The outcomes of this analysis will be used to propose technical, policy and economic interventions to improve the efficiency of operation of mini-grids, reduce up-front capital costs, enable more efficient supply regimes, and create better energy access outcomes.

Performance benchmarking has become a common business practice, which is undertaken to understand the current performance of a given unit of production or service compared to its peers. The theoretical idea comes from the concept of economic efficiency which in simple terms means producing as large an output as possible from a given set of inputs. The seminal work of Farrel (1957) introduced the concept of using the 'best results observed in practice' peers to estimate an efficient production function. This is explained in Figure 1 below using a two-input case. This paper applies the concepts of performance benchmarking to the delivery of electricity services via mini-grids in Sub-Saharan Africa.

Data envelopment analysis was initially proposed as a performance assessment methodology of a set of homogeneous decision-making units (DMUs) in the mid-1970s, through the work of Charnes, Cooper & Rhodes (1978). The authors presented a linear programming formulation of efficiency measurement that facilitated the development of a data-driven approach of performance measurement.

The main idea of DEA is to measure the relative technical efficiency of DMUs by a ratio of a weighted sum of outputs to a weighted sum of inputs, where the input and *output weights are selected in a manner that no DMU can have an efficiency score greater than unity (Charnes et al., 1994)*

This work has been expanded on significantly in the following decades. The initial CCR model assumed constant returns to scale, leading to Banker, Charnes & Cooper (1984) proposing an alternative model for estimating variable returns to scale, and a method for determining the most-productive-scale-size (MPSS) for decision-making units. The BCC model assumes a convexity constraint, ensuring that theoretical units are of similar scale sizes to the measured units, enabling the calculation of the MPSS for individual DMUs.

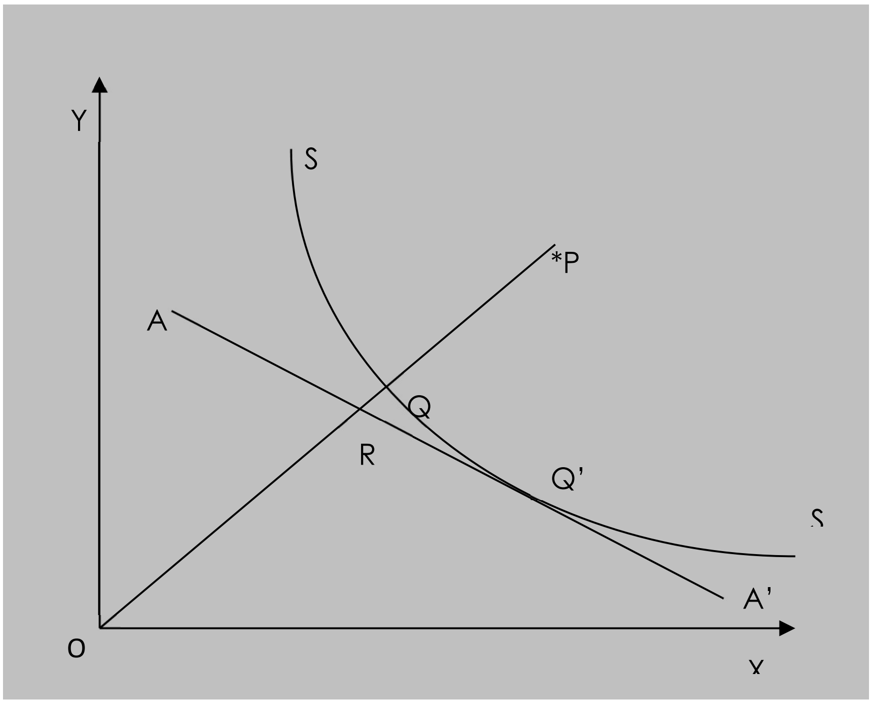


Fig. 1: Measurement of productive efficiency

Let us assume that SS' represents the various combinations of two inputs X and Y that an efficient firm uses to produce a unit of output (which in other words is known as the production possibility frontier). If a firm actually uses a combination of inputs represented by the point P, then the firm is using many more inputs compared to an efficient firm. To operate at the efficient level, it would have to use the combination of inputs which lies on the SS' curve. Assuming a constant returns to scale[1], this efficient combination is given by the point Q. This means that the efficient firm would produce (OP/OQ) times more output from the inputs used by the company producing at point P. The ratio OQ/OP gives the measure of technical efficiency. But the firm has to use the inputs in a cost-effective manner as well. If AA' has a slope equal to the ratio of the prices of the two factors, then cost minimisation requires that the firm produces where the cost function is tangent to the production possibility frontier (i.e. at Q'). This

[1] Which implies that if inputs are increased by a given factor, the output will also increase proportionately.

is different from Q, although both Q and Q' lie on the technically efficient production possibility. Therefore, if the firm chooses the input combinations represented by Q', it will reduce its cost by a factor OR/OQ, which is a measure of its price efficiency.

The overall efficiency is given by the product of technical efficiency and price efficiency [i.e. (OQ/OP)x(OR/OQ) = OR/OP]. Had the firm chosen its inputs in a technically efficient and cost-efficient manner, its costs would be only a fraction OR/OP of what they are now.

In practice, the production possibility function of a firm is not known and Farrel (1957) suggests that such a function can be constructed using observed data. The production possibility is then called the best practice frontier. The above approach has led to the development of benchmarking as a new field of study which is still used in business analysis and regulatory studies.

Section 2 below details our review of literature on data envelopment analysis applications to the performance analysis of renewable energy systems, and highlights the limited applications to-date in the analysis of mini-grid systems in developing countries. Section 3 describes our methodology, and how different estimation approaches can be used to determine best-practice frontiers using DEA. Section 4 shows an illustrative application of the methodology using an open-access dataset of mini-grids in developing countries from Duran & Sahinyazan (2021b). Section 5 discusses the results of our DEA modelling work on this dataset, and highlights the differences in terms of input- and output-oriented models and different returns-to-scale assumptions. Finally, Section 6 contains our conclusions from the research, and recommendations for policy-makers and future research.

2. LITERATURE REVIEW OF DEA APPLICATIONS TO RENEWABLE ENERGY SYSTEMS

Several applications of DEA to the productivity benchmarking of renewable energy systems exist in the literature. Agrell, Bogetoft & Tind (2005) use DEA to develop a benchmarking model to compare regulatory regimes across the Scandinavian electricity networks. Kuosamen, Saastomoinen & Sipiläinen (2013) compare three different assessment methodologies (DEA, stochastic frontier analysis and stochastic semi-nonparametric envelopment of data) in their analysis of benchmark regulation of the Finnish electricity distribution network. Gouveia et al (2015) use a value-based DEA method, which links traditional DEA with multiple criteria decision analysis to benchmark the performance of maintenance and outages repair for a Portuguese electricity distribution company. Arcos-Vargas, Núñez-Hernández and Villa-Caro (2017) assess 102 small electricity distributors in Spain using three separate input-oriented DEA models, considering both constant and variable returns to scale.

In the renewable energy space, authors have used DEA to investigate grid-scale and national-scale renewable energy installations and renewable sources, as well as benchmarking the performance of specific technologies across multiple installations, and latterly to assess the efficiency of different renewable energy mini-grid installations. Sueyoshi & Goto (2014) use both input- and output-oriented DEA models with variable returns to scale to analyse the performance of 160 grid-tied photovoltaic power plants in the United States and Germany. Wang et al (2017) use both stochastic frontier analysis and DEA to assess the environment-adjusted operational performance of photovoltaic plants in the United States. Wu et al (2018) assess photovoltaic poverty alleviation projects in China using a three-phase model, integrating DEA with Pearson correlation coefficients and a Tobit regression analysis. Indeed, Tobit regressions and DEA are frequently combined in the literature, with Wu et al (2016) using these combined methods to assess the efficiency of wind farms in China, and Sağlam (2017) using a 2-stage DEA-Tobit analysis to assess the productive efficiency of large-scale wind farms in the United States. Other forms of regression analysis have been combined with DEA in the literature, for example, Barros et al (2017) uses a virtual frontier dynamic range-adjusted DEA model alongside Simplex regression analysis to investigate the efficiency of Angolan hydroelectric power plants. Finally, Aziz & Chowdhury (2021) use a two-stage DEA model with Tobit regression to assess the performance of solar mini-grids in Bangladesh. The authors analyse the performance of twenty-one solar PV mini-grids using both the CCR and BCC models, perform a slacks analysis (also referred to as a slacks-based measure of efficiency (SBM)), and use Tobit regression to explore the relationship between dependent variables, efficiency scores from the DEA models, and exogenous factors. Slacks analysis in this instance refers to the assessment of the distance of each decision-making unit that is not on the efficiency frontier from the efficiency frontier. Both models used in Aziz & Chowdhury (2021) are input-oriented, as the total market size of an individual mini-grid is limited, and the objective is to deliver electricity services in the most efficient way.

DEA applications to renewable energy system performance benchmarking have several themes in common across the literature. DEA models used in the literature tend to be mixed, with constant and variable returns-to-scale models both used extensively for different purposes. Different types of returns-to-scale models are also commonly combined to derive different levels of efficiency measure, with pure technical efficiencies being analysed alongside scale efficiencies and slacks. DEA is also combined with regression analysis quite commonly in the literature. While this is not necessary for the methodology to produce robust results, it can offer some additional insights into the data: DEA in general produces more accurate results, but regression offers greater stability of accuracy of results (Thanassoulis, 1993). While it is common for models in the literature to feature multiple inputs and outputs, which is a strength of the methodology, Sueyoshi & Goto (2014) and Wang et al (2017) for example use a more limited set of input and output variables: three input and two outputs in the case of Sueyoshi & Goto (2014) and four input and one output in the case of Wang et al (2017).

From the review, we have identified a significant gap in the literature relating to performance analysis studies relating to energy and renewable energy in Sub-

Saharan African countries. Specifically for mini-grids, we have found only one comparable paper in Aziz & Chowdhury (2021) and for Sub-Saharan African nations, Barros et al (2017) is the sole comparable paper. DEA has been used to an extent in the performance analysis of energy production and distribution in industrialised countries, and for distributed renewable energy systems, but applications to the problem space of mini-grid performance are limited. This article seeks to address that gap by providing an indicative example of the application of the DEA methodology to the global mini-grids sector.

3. ESTIMATION APPROACHES FOR THE BEST PRACTICE FRONTIERS

In essence, the DEA methodology uses the observed data to identify the subset of DMUs that define the envelopment surface (efficient frontier). Those on this surface are efficient DMUs and any DMU not lying on the surface is inefficient. The DEA analysis provides information on the sources and amounts of inefficiency. the efficiency scores are relative measures – derived relative to other DMUs in the data set. This also implies that the efficiency scores will change if the sample size changes, or if the assumptions behind the scoring methodology change. In addition, the geometry of the envelopment surface is determined by the model chosen. For example, the CCR model results in a piecewise linear, constant-returns-to-scale envelope surface. The proportionality rule of constant returns to scale also implies the efficient DMUs will lie on the rays like the one shown in Fig. 1. The BCC model on the other hand uses a variable returns-to-scale envelope surface (Banker, Charnes and Cooper, 1984) which relaxes the ray assumption by adding a convexity constraint. Many more models and extensions have been explored in the literature but for this study, we are limiting ourselves to CCR and BCC models.

A further distinction is generally made with regards to optimisation of inputs or outputs. When the analysis aims to maximise the output for a given set of inputs, the output-oriented model is used. On the other hand, when inputs are maximised to produce a given output, the model is termed as an input-oriented model (Cooper, Seiford & Tone, 2007). In this study, we are using both the input-oriented and output-oriented models for comparing the performance of mini-grids.

Three separate aspects of mini-grid performance were considered in this study, namely technical, economic, and social aspects. Different input and output variables are needed when considering each of these dimensions:

1) For the technical performance of a mini-grid, we considered output variables such as generation per unit of capacity, user per unit capacity, given the installed capacity, its renewable energy share and other available data (such as hours of service and employee per unit capacity). Given the constraints on available data to perform this analysis, three technical dimensions were selected to take forward: the

capacity per person, the renewable energy share of the mini-grid system, and the age of the system.

2) For the economic analysis, cost per unit of output or LCOE is a desired output variable. Conventional input variables include installation cost per unit of capacity, employee related costs per unit of capacity, fuel related costs per unit of output and so on: for this analysis, we used cost per watt delivered as an economic output variable

3) For social performance analysis, data for suitable variables are not easily available. In an output-oriented analysis, in line with the universal electrification target, the share of households gaining access in the community can be considered. Reduced dependence on traditional fuels or % increase in study time could be another desired outcome to consider. The capacity of the mini-grid and its renewable energy share could be the inputs for this dimension. Data availability remains an important challenge in this study. Commonly reported data include capacity, renewable energy share and number of users. Cost data and social data are more difficult to find. Survey data can provide information at a given point in time and the data set can be limited as well. Faced with this challenge, we have kept the analysis simple and exploratory in this study, and restricted the analysis to technical and economic dimensions.

4. ILLUSTRATIVE CASE APPLICATIONS

Duran and Sahinyazan (2021a) reported a global dataset of mini-grid projects covering both developed and developing countries. The data contains information about project location, year of construction, technology type, capacity, population served, and project cost estimates, among others. The data was used to conduct an econometric analysis of mini-grid projects which was reported in Duran and Sahinyazan (2021b). This is a rich dataset that is available publicly and is suitable for illustrating the DEA application. This section presents the details of this analysis.

4.1 Data selection for the application

The above dataset includes mini-grids from developed countries, which are likely to have different characteristics compared to the mini-grids for electricity access being used in developing countries. As a first step, we have removed any project information from the developed countries. This reduced the sample to 83 projects.

We then extracted information relating to ownership type, installation date, installed capacity, Renewable energy fraction in the capacity, population served and installation cost of the project. Each project was identified using a code indicated the country of the project, and its identification in the main data file. For example, In-9 implies the project was located in India and it came from the 9th row of the metadata file. The ownership type was then coded as follows: private as 1, public as 2, PPP as 3, community as 4. The age of each project was identified from the difference between

2020 and the installation date. Using installed capacity and population served, the capacity per person was calculated. In the absence of information on power produced from the plant, the cost per Watt (calculated from the installation cost and installed capacity) is used as a proxy for the cost of generation. This is used as the output variable and the remaining data was used as input variables, apart from the ownership type, which was used as a non-controllable variable.

For generation capacity per capita, this variable represents the ability of a mini-grid to supply adequate power to the users of the system. The renewable energy share represents the environmental sustainability and low-carbon nature of the system. The age of the facility is used to capture the status of the technology, as older systems are correlated with less clean technologies and lower reliability. The cost per watt as an output is used to capture the affordability of the system for developers.

After processing data, it was noticed that two variables were reporting errors due to missing data. Accordingly, these points were removed from the set used for the analysis. The data used for this case is placed in Annex 1, which contains data for 81 projects. Ramanathan (2003) suggests that the number of DMUs in a sample dataset, in order to be representative, should be greater than three times the sum of input and output variables, or larger than the product of the number of inputs and outputs, both of which are true for this dataset. Table 2 presents the variables used in the analysis of this dataset. To perform the analysis, an open-source software package, OSDEA, was employed, and results were further analysed in MS Excel (OSDEA, 2023).

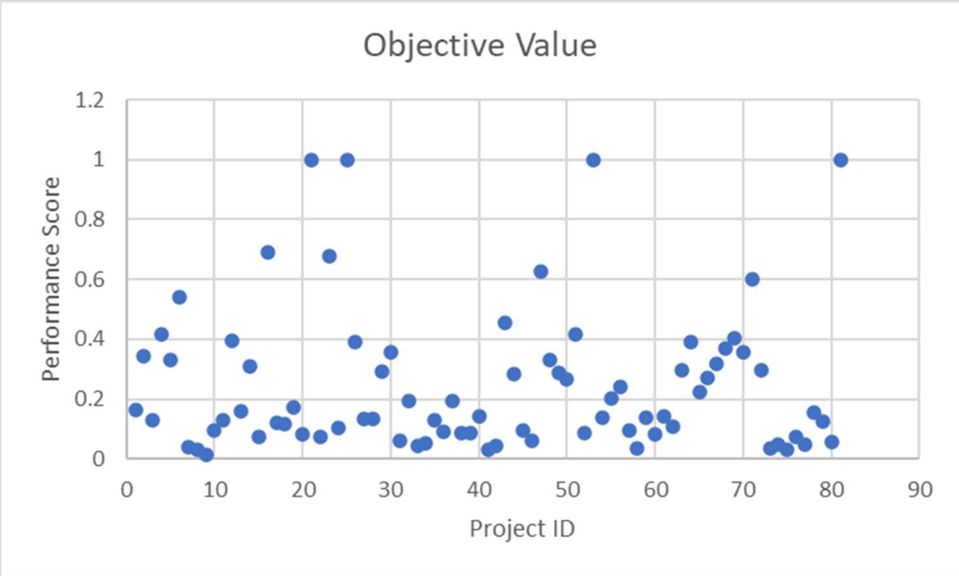
Table 2: Variables used in the analysis of Duran & Sahinyazan (2021a)

Variable	Unit
Input 1	Capacity/person (W/capita)
Input 2	Renewable Energy Share (0 – 1)
Input 3	Age (integer)
Non-controllable Input 1	Ownership model (1, 2, 3, 4 for private, public, PPP or community)
Output 1	Cost/watt (USD/W)

4.2 Results from the CCR analysis

First, we have considered the output-oriented CCR model with cost per Watt used as the output variable. This model optimises for increased outputs for a constant level of inputs. The three inputs included were capacity per person, RE share, and age of the installation, with ownership type as a fourth, non-controllable input. Using the above combination of inputs and output, four plants were found to be efficient. Four others received a score between 0.6 and 0.8. Another 8 plants received a score between 0.4 and 0.6. The majority of the plants scored below 0.4. The scatter plot of the efficiency scores is presented in Fig. 1.

Figure 1: Scatter plot of output-oriented CCR efficiency



As indicated previously, the efficient plants form the best practice envelope and, in our case, four plants were on this envelope. All other plants are compared against these efficient plants. Each plant is placed in a peer group composed of one or more of the efficient plants. This peer group represents the plant on the efficiency frontier that the plant in question is most similar to. The frequency of plants under different groups for the CCR analysis is shown in Table 3. Nam-104 has the greatest number of peers, followed by the group composed of Col-45 and Nam-104, and the group composed of Col-45 and N-76. This suggests that the greatest number of plants are most similar to Nam-104 in terms of their efficiency.

Table 3: Peer groups and plant distribution

Peer Group	Nam-104	N-76	Per-41	Col-45	Col-45 & N-76	Col-45 & Nam-104	Per-41 & Nam-104	Per-41 & N-76	Col-45, N-76 & Nam-104	Per-41, N-76 & Nam-104	All Efficient Mini-Grids
Mini-Grids in Group	23	1	1	2	17	18	11	4	2	1	1

The closer to 1 the lambda value is for a given plant in relation to its peers, the closer to the peer the efficiency of the plant is, and the less the plant needs to increase its outputs to reach the efficient frontier for this output-oriented model. For the largest peer group, the peers of Nam-104, the highest lambda value reported was 0.5 for Ton-34, In-68 and CV-85, while the lowest non-zero reported value was 0.04, for Ken-58.

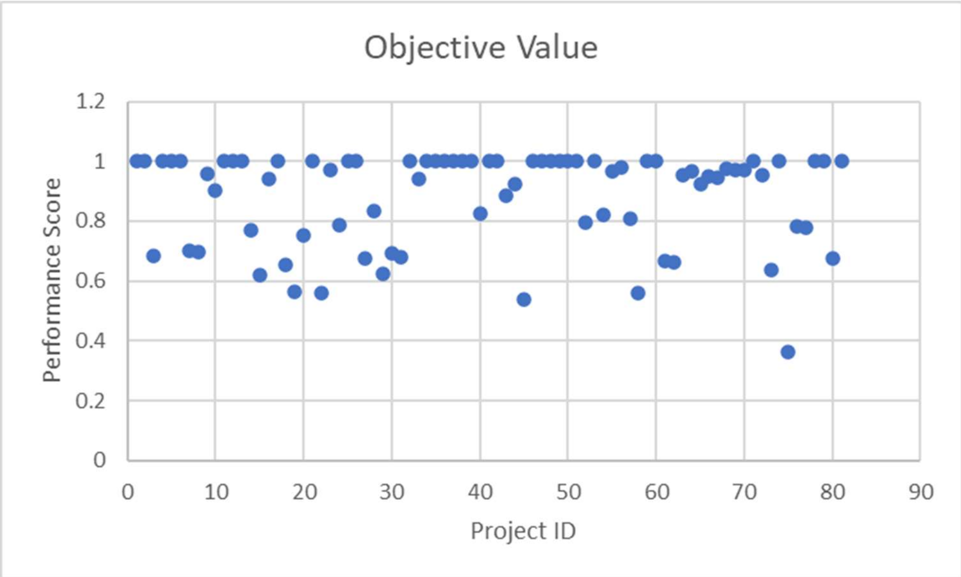
Slacks, when used in relation to models like CCR and BCC, are the additional improvements in input reduction or output maximisation over that which is implied by the gap in efficiency score, which deals with increases in outputs or decreases in inputs equally across all input and output variables. The four efficient plants have no slack available in their input variables, meaning they are operating efficiently across all inputs. Other plants have some slacks, but the level of input slack varies by plant and by input, depending on the magnitude of the input variables. AS-7 illustrates this variance well, with slacks of 2,275.48 W/person in capacity, and 0.5 in terms of renewable energy share. This means AS-7 could maintain its efficiency while dramatically reducing its capacity in terms of watts per person, as well as reducing the share of renewable energy in the plant generation mix. This also highlights a limit of the analytical method: higher renewable energy shares do not necessarily translate to more efficient plants in the analysis, and this needs to be accounted for when analysing the results. For constant returns-to-scale models like the CCR model, the efficiency scores for the output and input-oriented variances are the same, as the efficiency frontier does not change with regard to the orientation of the model. The peer groups for this analysis are also identical to the input-oriented model presented in table 3. Examining the lambda values, however, provides additional insight into how the sample of DEAs is performing in relation to the efficiency frontier. For Nam-104 again, the highest lambda value reported was 0.12 for Tuv-53, and the lowest non-zero lambda was 0.0009 for MAU-13.

The overall trend of lambda values being smaller (closer to 0) is mirrored in the slacks for input-oriented model. Comparing AS-7 again, the W/person capacity slack is 293.01, and the renewable energy share slack has fallen to 0.06, both reduced dramatically from the output-oriented model. This indicates that, while individual plants themselves may have more to improve under an input-oriented model, and are further away from their peers, they are operating efficiently for their scale size under a constant returns-to-scale assumption.

4.3 Results from the BCC Analysis

The Banker, Charnes and Cooper model (BCC) represents an efficiency analysis from a variable returns-to-scale perspective. While the CCR model gives a pure technical efficiency measure, the BCC model accounts for the scale size of individual DMUs, and accounts for efficiency at all scale sizes, allowing for a determination of the most-productive-scale-size (MPSS) of DMUs. If DMUs are operating at a scale size that is larger or smaller than what would be optimally productive for them, the BCC model accounts for and captures this inefficiency.

Figure 2: Scatter plot of input-oriented BCC Efficiency

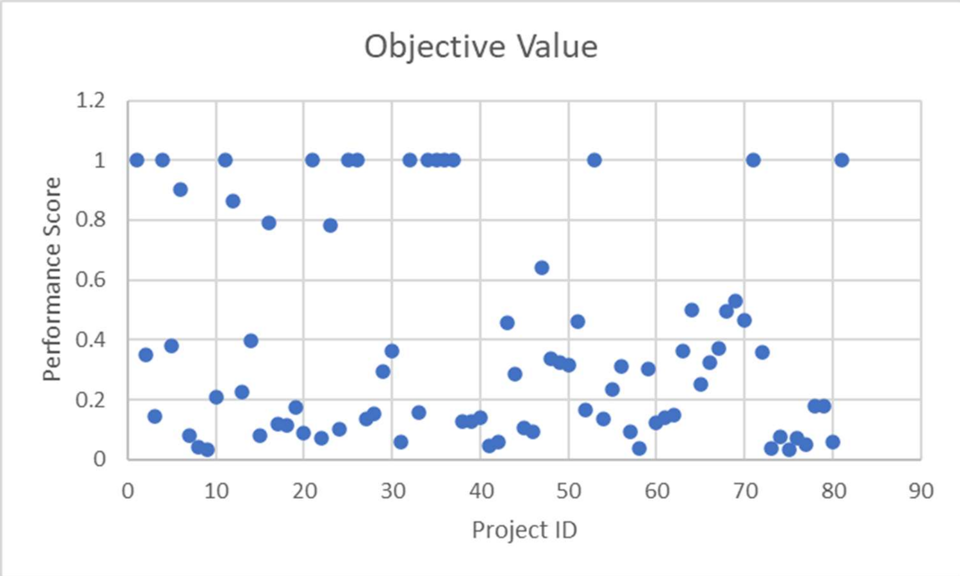


34 plants achieved an efficiency score of 1 in the input-oriented BCC analysis, however only 14 of these plants are defined as efficient in the software output. This is due to the presence of output slacks for the plants with perfect efficiency scores: an example of this is H-6, which has a BCC efficiency of 1, but has input slacks in plant age, and output slacks in cost per watt delivered. Input-oriented BCC efficiency scores are significantly higher than those for the CCR analysis, which is consistent with the variable returns-to-scale assumptions inherent in the BCC model. The majority of plants score above 0.6 in this analysis, with some outliers: the worst-performing plant, Tan-98, has an efficiency score of 0.36.

Compared to the CCR model, which had 11, the input-oriented BCC analysis has 39 separate peer groups. The largest peer group was for Per-41, which has 16 peers, followed by a combined peer group of Per-41, Ken-57 and MM-94. 27 of these 39 peer groups had a single member, indicating a greater overall spread of peers on the efficiency frontier under the variable returns-to-scale assumption.

For Per-41, with the largest peer group, 16 plants had a lambda value of 1, indicating they were equally as efficient, while the largest non-zero lambda was 0.03. The 32 plants with non-zero lambda values to Per-41 exhibited an even spread across the range.

Figure 3: Scatter plot of output-oriented BCC efficiency



14 plants are classed as efficient under the output-oriented BCC analysis. No plants in this analysis have perfect efficiency scores but are not classed as efficient, indicating no output slacks for efficient plants at these scale sizes.

There are 33 peer group combinations for different plants in this analysis. Per-41 again has the largest peer group, with 16 peers, followed by a group of Col-45 and Nam-104 together, with 11. 23 of these 33 peer groups have a single member. Of the non-zero, non-one lambda values for Per-41, the largest is 0.96, with the smallest being 0.006. Seven plants have a lambda value of 2/3 (0.667).

4.4 Scale Efficiency of Mini-Grids

Using the CCR and BCC model outputs, we can now calculate the scale efficiency of the sampled mini-grids. Constant returns-to-scale efficiency scores, such as the outputs of the CCR models, represent the overall efficiency of the mini-grid, including both technical efficiency and scale efficiency. Variable returns-to-scale models, such as the outputs of the BCC models, represent the pure technical efficiency of the mini-grid, regardless of their current scale size. If we therefore calculate the ratio of CCR efficiency to BCC efficiency, we can determine the scale efficiency of the mini-grids, and investigate the most-productive scale size for the assessed mini-grids. The results for the input-oriented scale efficiency and output-oriented scale efficiency analysis are presented in Figure 4 and 5 below:

Figure 4: Scatter plot of input-oriented scale efficiency

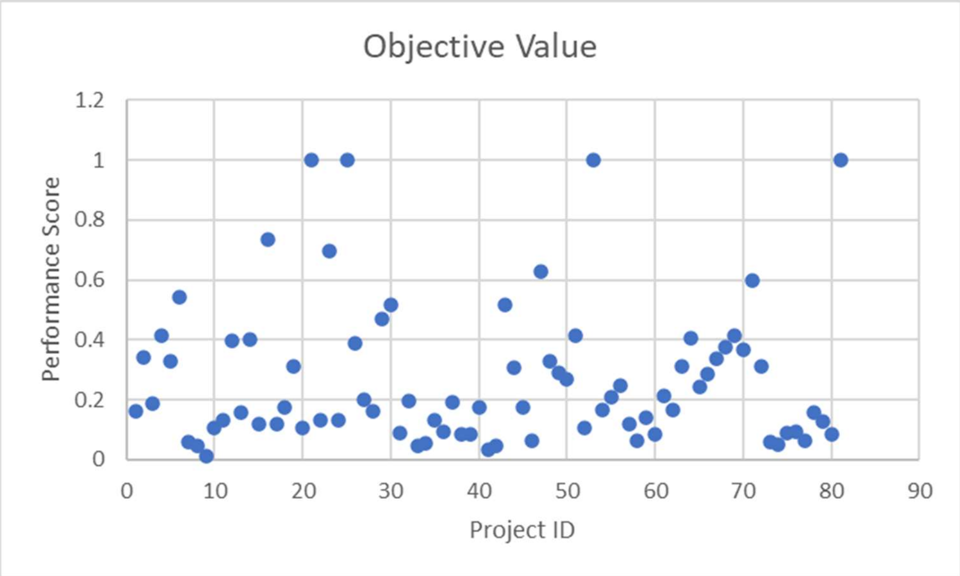
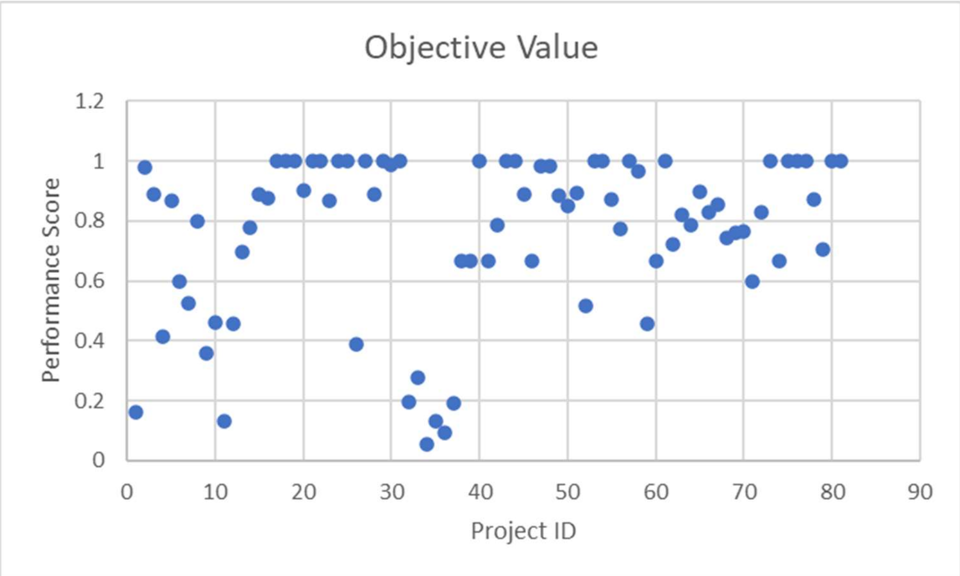


Figure 5: Scatter plot of output-oriented scale efficiency



In these analyses, the higher the scale efficiency score, the closer the plant is to operating at its most productive scale size.

Table 3 presents the full results of the analysis, including CCR efficiency, input- and output-oriented BCC efficiency, and scale efficiency for the 81 mini-grids analysed.

Table 4: Full DEA Results

Mini-Grid	CCR Efficiency	BCC-Input Efficiency	BCC-Output Efficiency	Scale Efficiency – Input	Scale Efficiency - Output
H-5	0.162	1.000	0.162	0.162	1.000
H-6	0.342	1.000	0.342	0.342	0.349
AS-7	0.129	0.683	0.189	0.129	0.145

In-8	0.415	1.000	0.415	0.415	1.000
In-9	0.330	1.000	0.330	0.330	0.381
In-10	0.541	1.000	0.541	0.541	0.903
Ma-11	0.042	0.702	0.060	0.042	0.080
CV-12	0.033	0.699	0.047	0.033	0.041
MAU-13	0.012	0.960	0.013	0.012	0.034
Per-16	0.097	0.902	0.107	0.097	0.210
Niu-17	0.131	1.000	0.131	0.131	1.000
H-20	0.396	1.000	0.396	0.396	0.866
In-21	0.158	1.000	0.158	0.158	0.227
Ch-24	0.309	0.768	0.403	0.309	0.398
Ton-34	0.072	0.620	0.117	0.072	0.081
Ton-36	0.693	0.943	0.735	0.693	0.792
Ind-37	0.120	1.000	0.120	0.120	0.120
Gua-38	0.115	0.656	0.176	0.115	0.115
Dom-Hai-39	0.175	0.563	0.310	0.175	0.175
Col-40	0.081	0.751	0.107	0.081	0.090
Per-41	1.000	1.000	1.000	1.000	1.000
Ecu-42	0.073	0.559	0.130	0.073	0.073
Mex-43	0.676	0.972	0.696	0.676	0.781
Col-44	0.103	0.785	0.131	0.103	0.103
Col-45	1.000	1.000	1.000	1.000	1.000
Chil-46	0.389	1.000	0.389	0.389	1.000
Nica-47	0.136	0.674	0.201	0.136	0.136
Per-48	0.135	0.834	0.162	0.135	0.152
Fij-52	0.293	0.623	0.471	0.293	0.293
Tuv-53	0.359	0.695	0.516	0.359	0.363
Van-54	0.061	0.678	0.089	0.061	0.061
Ken-55	0.196	1.000	0.196	0.196	1.000
Ken-56	0.044	0.942	0.047	0.044	0.159
Ken-57	0.054	1.000	0.054	0.054	1.000
Ken-58	0.131	1.000	0.131	0.131	1.000
Ken-59	0.093	1.000	0.093	0.093	1.000

Ken-60	0.192	1.000	0.192	0.192	1.000
In-61	0.086	1.000	0.086	0.086	0.128
In-62	0.086	1.000	0.086	0.086	0.128
Ma-63	0.142	0.823	0.173	0.142	0.142
In-64	0.031	1.000	0.031	0.031	0.047
In-65	0.046	1.000	0.046	0.046	0.058
In-66	0.456	0.885	0.515	0.456	0.456
In-67	0.284	0.925	0.307	0.284	0.284
In-68	0.094	0.540	0.174	0.094	0.106
In-69	0.062	1.000	0.062	0.062	0.093
N-70	0.628	1.000	0.628	0.628	0.639
N-71	0.329	1.000	0.329	0.329	0.335
N-72	0.288	1.000	0.288	0.288	0.325
N-73	0.267	1.000	0.267	0.267	0.314
N-74	0.415	1.000	0.415	0.415	0.463
Fij-75	0.086	0.794	0.108	0.086	0.166
N-76	1.000	1.000	1.000	1.000	1.000
CN-77	0.136	0.820	0.166	0.136	0.136
Ken-78	0.203	0.968	0.210	0.203	0.233
Ken-79	0.241	0.981	0.246	0.241	0.313
Ug-80	0.095	0.810	0.117	0.095	0.095
Ug-81	0.035	0.562	0.061	0.035	0.036
Ug-82	0.139	1.000	0.139	0.139	0.304
Ug-83	0.082	1.000	0.082	0.082	0.123
Ug-84	0.142	0.668	0.212	0.142	0.142
CV-85	0.108	0.661	0.164	0.108	0.150
MM-86	0.298	0.955	0.312	0.298	0.363
MM-87	0.393	0.966	0.407	0.393	0.501
MM-88	0.226	0.924	0.244	0.226	0.251
MM-89	0.270	0.952	0.284	0.270	0.325
MM-90	0.319	0.943	0.338	0.319	0.373
MM-91	0.368	0.976	0.377	0.368	0.495
MM-92	0.402	0.972	0.414	0.402	0.529

MM-93	0.356	0.971	0.366	0.356	0.466
MM-94	0.599	1.000	0.599	0.599	1.000
MM-95	0.297	0.953	0.312	0.297	0.358
Tan-96	0.037	0.638	0.059	0.037	0.037
Tan-97	0.050	1.000	0.050	0.050	0.075
Tan-98	0.032	0.363	0.088	0.032	0.032
Tan-99	0.073	0.781	0.093	0.073	0.073
Tan-100	0.051	0.776	0.065	0.051	0.051
Tan-101	0.156	1.000	0.156	0.156	0.179
Tan-102	0.126	1.000	0.126	0.126	0.179
Tan-103	0.058	0.676	0.086	0.058	0.058
Nam-104	1.000	1.000	1.000	1.000	1.000

5. DEA AND MINI-GRID PERFORMANCE BENCHMARKING: DISCUSSION

For the selected set of mini-grid DMUs from Duran & Sahinyazan (2021a), the CCR and BCC model results above provide some insights into how the productive efficiency of mini-grids can be improved. There are also interesting differences in performance depending on the geographic region the mini-grid is located in, as well as the ownership model that the mini-grid uses.

5.1 CCR, BCC & Scale Efficiency Discussion

The CCR analysis produced only four efficient DMUs out of the sample of 81, which is significantly less than the number produced in the BCC analysis which produced 14 efficient DMUs. While this is expected, the scale of inefficiency in mini-grids in the CCR model was not: the majority of plants scored below 0.4 in the CCR model, with only 12 of the 81 managing to score above this. This indicates that the majority of the mini-grids analysed are operating inefficiently, assuming constant returns-to-scale. The BCC analysis with its variable returns-to-scale assumption indicates that more mini-grids are operating efficiently, particularly in an input-oriented analysis, where the majority of mini-grids are above 0.6 efficiency rating. This indicates output efficiency is good among the corpus, however input efficiency, as shown by the output-oriented model, is worse overall, with the majority of plants scoring below 0.4. This indicates further input efficiency is needed, to minimise inputs for the specified output levels. More efficient DMUs being present in a variable returns-to-scale model is expected due to the model accounting for variable returns-to-scale.

The scale efficiency results, however, show that there are significant efficiencies to be found in operating at more productive scale sizes. The output-oriented models suggest that overall scale efficiency across the corpus is acceptable, but there remain 33 DMUS with scale efficiencies below 0.8. With an input-oriented perspective, no DMUs apart from the four DMUs on the efficiency frontier in the CCR model have a scale efficiency above 0.8, indicating that scale size issues are the driver of inefficiency in these mini-grids. In terms of slacks also, both input and output slacks exist for the orientations of the two models used. Input slacks are most common in the capacity per person of the mini-grids, and output slacks exist for the cost per watt delivered in both input-oriented models. This indicates that even if mini-grids were operating at their most productive scale size, there are further efficiency improvements to be found in optimising the capacity per customer served in mini-grids.

5.2 Geographic Differences in Mini-Grid Performance

Of the mini-grids on the efficiency frontier in the CCR model, two are African mini-grids and two are Latin/South American or Caribbean mini-grids. Specifically, one mini-grid from Nigeria and Namibia, and one mini-grid from Peru and Colombia are on the efficiency frontier under the CCR model, with no Asia-Pacific mini-grids being fully efficient. However, efficiency scores under the CCR model are higher in the Asia-Pacific mini-grids, with greater numbers of poorly-performing mini-grids in the other two global regions. Overall, however, CCR efficiency scores are low globally.

For the BCC results, input- and output-oriented models will be considered separately, and exhibit different results. 9 out of the 31 African mini-grids exhibit input-oriented BCC efficiency scores of below 0.8, with 17 being on the efficiency frontier, the best-performing region in this analysis. 11 of the 34 Asia-Pacific mini-grids are efficient under the input-oriented BCC model, with 8 out of the 34 having scores below 0.8, meaning overall efficiency scores are higher than African mini-grids, but peak scores are lower. 5 out of the 16 Latin/South American and Caribbean mini-grids are efficient under BCC-input, with 7 of the 16 having scores below 0.8.

Similarly to the CCR analysis, output-oriented BCC scores are low for the majority of mini-grids, however all regions have some mini-grids on the efficiency frontier. 7 of the 31 African mini-grids are efficient under this analysis, compared to 3 of the 34 Asia-Pacific mini-grids and 4 of the 16 Latin/South American and Caribbean mini-grids. Percentage-wise, Latin/South America and the Caribbean performs best, however the Asia-Pacific mini-grids have the greatest number above 0.4, and between 0.2 and 0.4, while the majority of African mini-grids score below 0.2, and all other Latin/South American and Caribbean mini-grids score below 0.4, with 8 of 16 below 0.2. This indicates that globally, output-oriented efficiency under the BCC model is low, with the Asia-Pacific region having a slight advantage, but all global regions assessed have room for improvement.

5.3 Ownership Models and Mini-Grid Performance

The original data set also allows us to perform some analysis of the relative efficiencies of different mini-grids by ownership model. Four different ownership models are represented in the sample, being privately-owned mini-grids, publicly-owned, community-owned and public-private partnerships. PPPs are the least well-represented in the dataset, with just five mini-grids under this ownership model, but otherwise the sample contains 21 publicly-owned mini-grids, 24 privately-owned and 31 community-owned. Overall, community and privately-owned mini-grids perform best under the CCR model, with publicly-owned mini-grids performing less well overall. Under an input-oriented BCC model, privately-owned mini-grids perform the best, with every example in the sample being on the efficiency frontier under this orientation. Publicly-owned mini-grids also performed very well in this orientation, and while the overall performance of community mini-grids is still good, it was the worst-performing out of the three ownership types with sufficient sample sizes. However, community-owned mini-grids performed the worst in the output-oriented BCC model, with publicly-owned mini-grids performing the best.

In terms of scale efficiency, a notable result is that community-owned mini-grids operate at their most productive scale size much more frequently that other ownership types under an output-oriented configuration, with 23 of the 31 sampled operating at above 0.8 scale efficiency, and 18 at the most productive scale size. This compares to 1 of 24 private mini-grids operating at their MPSS, and 3 of 21 public mini-grids. For an input-oriented configuration, scale efficiencies are low throughout, but community-owned mini-grids again show a performance advantage in terms of scale size. 19 of 31 community-owned mini-grids have a scale efficiency measure of 0.2 or above, compared to 12 of 24 privately-owned mini-grids and just 5 of 21 publicly-owned mini-grids.

6. CONCLUSIONS

This paper has used the open-access dataset from Duran & Sahinyazan (2021b) to perform a data envelopment analysis, determining the relative production efficiencies of mini-grids in developing countries across the world. Data for 81 mini-grids was extracted, and two separate data envelopment analysis models were used to analyse the dataset. The Charnes, Cooper & Rhodes (CCR) model offered an analysis under a constant returns-to-scale assumption, while the Banker, Charnes and Cooper (BCC) model offered an analysis with a variable returns-to-scale assumption. This allowed for the determination of the most-productive-scale-size for the mini-grids analysed, by comparing the pure technical efficiency given by the BCC model with the technical and scale efficiency of the CCR model. Four inputs and one output variable were considered for this analysis, with the capacity per person served by the mini-grid, the renewable energy share of the mini-grid and the age of the mini-grid being used alongside a code for the ownership model of the mini-grid as inputs, and the cost per watt delivered as the single output.

This analysis has shown that there are significant issues present with the productive efficiency of mini-grids in developing countries. Compared to their peers in the dataset, the majority of mini-grids are inefficient, with a large number of mini-grids being very inefficient compared to their peers. The input-oriented models in particular highlight this inefficiency: input-oriented scale efficiency is low across the corpus, indicating that the majority of mini-grids are operating far away from their most productive scale size. Moving forward, the mini-grid sector in developing countries needs to assess the scale of their operations, and determine whether increasing or decreasing returns to scale are present to expand or diversify their operations as appropriate.

DEA as a methodology shows promise in the analysis of productive efficiency in the mini-grids sector. Few articles in the literature have addressed this topic to date, the notable exception being Aziz & Chowdhury (2021). Access to reliable quantitative data is a challenge: Aziz & Chowdhury (2021) addressed this barrier by investigating a context where a public utility is the primary developer of mini-grids, and thus has access to data as required to complete the analysis. Our secondary data analysis had to optimise for the data that was available, and diversified public and private-sector developer contexts, such as much of Sub-Saharan Africa, present a challenge to the collection of reliable quantitative data. This presents barriers for implementing DEA as a methodology for productive efficiency analysis going forward, which need to be addressed if the sector is to become more efficient, deliver energy services on a more cost-effective and productive basis, and achieve the Sustainable Development Goals for energy access by 2030.

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Annex 1: Mini-grid data extracted from the meta-analysis dataset.

DMU-ID	Ownership	Installation date	Capacity (W)	RE share	Cost (USD 2020)	population	Capacity/person (W)	RE Share	Age	Ownership	cost/W (USD 2020)
H-5	private	2015	400	0.5	2,100,000	5500	72.72727273	0.5	5	1	5.25
H-6	private	2016	2.7	1	19,902	250	10.8	1	4	1	7.371111
AS-7	public	2016	1400	1	8,600,000	600	2333.333333	1	4	2	6.142857
In-8	private	2014	1.2	1	9,341	375	3.2	1	6	1	7.784167
In-9	private	2014	1	1	6,906	110	9.090909091	1	6	1	6.906
In-10	private	2014	1.2	1	12,721	220	5.454545455	1	6	1	10.60083
Ma-11	public	2012	2612	0.48	6,800,000	3746	697.2770956	0.48	8	2	2.603369
CV-12	ppp	2011	24290	0.24	25,000,000	84229	288.3804865	0.24	9	3	1.02923
MAU-13	public	2010	13400	0.08	1,700,000	37000	362.1621622	0.08	10	2	0.126866
Per-16	public	2014	11.5	0.57	49,147	255	45.09803922	0.57	6	2	4.273652
Niu-17	public	2018	3000	0.2	8,400,000	1624	1847.29064	0.2	2	2	2.8
H-20	private	2015	123	0.76	1,500,000	2790	44.08602151	0.76	5	1	12.19512
In-21	private	2014	100	1	492,819	2200	45.45454545	1	6	1	4.92819
Ch-24	community	2010	175	0.14	982,419	105	1666.666667	0.14	10	4	5.613823
Ton-34	public	2013	512	1	2,400,000	3000	170.6666667	1	7	2	4.6875
Ton-36	public	2017	550	1	16,000,000	7212	76.26178591	1	3	2	29.09091
Ind-37	community	2018	1200	1	8,800,000	1840	652.173913	1	2	4	7.333333
Gua-38	community	2014	90	1	872,246	804	111.9402985	1	6	4	9.691622
Dom-Hai-39	community	2008	1300	1	17,000,000	20000	65	1	12	4	13.07692

Col-40	public	2015	191	1	823,345	1853	103.0760928	1	5	2	4.310707
Per-41	private	2017	20.55	1	445,199	1850	11.10810811	1	3	1	21.66418
Ecu-42	community	2012	12.27	1	85,399	80	153.375	1	8	4	6.959984
Mex-43	ppp	2013	187.5	1	3,600,000	30000	6.25	1	7	3	19.2
Col-44	community	2016	8	1	59,896	76	105.2631579	1	4	4	7.487
Col-45	community	2018	7.85	1	480,675	250	31.4	1	2	4	61.23248
Chil-46	private	2000	27	0.56	340,601	213	126.7605634	0.56	20	1	12.61485
Nica-47	community	2007	220	1	1,900,000	5900	37.28813559	1	13	4	8.636364
Per-48	public	2016	20	1	129,054	200	100	1	4	2	6.4527
Fij-52	community	2013	20	1	443,198	300	66.66666667	1	7	4	22.1599
Tuv-53	public	2009	46	1	962,501	600	76.66666667	1	11	2	20.92393
Van-54	community	2014	75	1	327,092	1300	57.69230769	1	6	4	4.361227
Ken-55	ppp	2015	46.8	0.85	304,924	4000	11.7	0.85	5	3	6.51547
Ken-56	public	2011	3400	0.15	2,900,000	41000	82.92682927	0.15	9	2	0.852941
Ken-57	public	2013	3460	0.1	2,400,000	50400	68.65079365	0.1	7	2	0.693642
Ken-58	public	2011	260	0.04	176,430	1350	192.5925926	0.04	9	2	0.678577
Ken-59	public	2013	570	0.09	616,382	2520	226.1904762	0.09	7	2	1.081372
Ken-60	public	2012	860	0.07	1,500,000	6890	124.8185776	0.07	8	2	1.744186
In-61	private	2006	43	1	119,476	336	127.9761905	1	14	1	2.778512
In-62	private	2006	150	1	416,777	178	842.6966292	1	14	1	2.778513
Ma-63	community	2005	5	1	34,777	300	16.66666667	1	15	4	6.9554
In-64	private	2010	50	1	50,478	436	114.6788991	1	10	1	1.00956
In-65	private	2012	32	1	40,492	989	32.35591507	1	8	1	1.265375
In-66	public	2002	2	1	35,233	179	11.17318436	1	18	2	17.6165

In-67	public	2010	4.5	1	45,430	587	7.666098807	1	10	2	10.09556
In-68	public	2005	120	1	730,016	1029	116.6180758	1	15	2	6.083467
In-69	private	2012	32	1	64,787	553	57.86618445	1	8	1	2.024594
N-70	private	2013	6	1	83,100	480	12.5	1	7	1	13.85
N-71	private	2015	9	1	65,341	720	12.5	1	5	1	7.260111
N-72	private	2015	34	1	239,583	1600	21.25	1	5	1	7.046559
N-73	private	2015	40	1	272,254	1600	25	1	5	1	6.80635
N-74	private	2015	24	1	240,909	1180	20.33898305	1	5	1	10.03788
Fij-75	public	1997	290.6	0.31	1,000,000	2000	145.3	0.31	23	2	3.441156
N-76	public	2006	3	1	106,268	5000	0.6	1	14	2	35.42267
CN-77	ppp	2003	31.05	1	206,575	1800	17.25	1	17	3	6.652979
Ken-78	community	2012	13.5	1	75,885	3000	4.5	1	8	4	5.621111
Ken-79	community	2014	21.9	1	119,389	5000	4.38	1	6	4	5.451553
Ug-80	community	2015	13.5	1	73,509	500	27	1	5	4	5.445111
Ug-81	ppp	2012	32	1	91,623	172	186.0465116	1	8	3	2.863219
Ug-82	private	2016	288.8	0.79	1,300,000	2000	144.4	0.79	4	1	4.501385
Ug-83	private	2006	250	1	668,013	470	531.9148936	1	14	1	2.672052
Ug-84	community	2014	40	1	424,306	615	65.04065041	1	6	4	10.60765
CV-85	public	2012	60	0.67	421,584	450	133.3333333	0.67	8	2	7.0264
MM-86	community	2016	9.76	1	80,659	977	9.989764585	1	4	4	8.264242
MM-87	community	2016	9.76	1	96,683	1138	8.576449912	1	4	4	9.906045
MM-88	community	2016	4.88	1	39,469	336	14.52380952	1	4	4	8.08791
MM-89	community	2016	13	1	100,673	1237	10.50929669	1	4	4	7.744077
MM-90	community	2016	10.8	1	106,018	925	11.67567568	1	4	4	9.816481

MM-91	community	2016	6	1	50,047	836	7.177033493	1	4	4	8.341167
MM-92	community	2016	7.2	1	68,624	931	7.733619764	1	4	4	9.531111
MM-93	community	2016	12.96	1	110,018	1654	7.835550181	1	4	4	8.489043
MM-94	community	2016	8.7	1	88,583	2170	4.00921659	1	4	4	10.18195
MM-95	community	2016	6.48	1	54,667	625	10.368	1	4	4	8.436265
Tan-96	community	2012	300	1	762,522	6199	48.3949024	1	8	4	2.54174
Tan-97	private	2015	500	1	816,761	3789	131.9609396	1	5	1	1.633522
Tan-98	community	2001	250	1	968,469	1390	179.8302403	1	19	4	3.873876
Tan-99	community	2006	10	1	38,738	460	21.73913043	1	14	4	3.8738
Tan-100	community	2015	210	1	668,013	5896	35.61736771	1	5	4	3.181014
Tan-101	private	2013	44	1	170,387	1950	22.56410256	1	7	1	3.872432
Tan-102	private	2013	35.2	1	136,310	800	44	1	7	1	3.872443
Tan-103	community	2013	8.8	1	34,078	200	44	1	7	4	3.8725
Nam-104	community	2006	1.6	1	207,337	8	200	1	14	4	129.5856