Gauging Energy Poverty in Developing Countries through Electricity Access

Carlo Drago
University Niccolò Cusano
Andrea Gatto (andrea.gatto@uniparthenope.it)
Natural Resources Institute, University of Greenwich https://orcid.org/0000-0003-1005-3571

Article

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Abstract

Energy poverty is a crucial development issue though is ambiguously conceived. In many parts of the world, energy poverty is a severe problem, particularly amongst the vulnerable and developing countries. When impoverished people do not have adequate access to energy, they will not be able to generate the power they need to lift themselves out of poverty and often get proper food, education, health and sanitation, infrastructures and basic daily and development needs. With the advantage of interval-based composite indicators and triplex representations of the intervals as a sensitivity analysis, we measure and assess developing countries' electricity access as a proxy of energy poverty. The proposed quantitative approach is particularly innovative because it adequately gauges robust measures of electricity access and the level of resilience and vulnerability of energy access in the developing world. Our conclusion based on the comparison of the different representations allows identifying a cluster of developing countries showing higher international vulnerability, whilst other countries display higher electricity access resilience.

JEL codes: C15 [Statistical Simulation Methods: Single Equation Models, Monte Carlo Methods, Bootstrap Methods] C43 [Index numbers and aggregations] I32 [Measurement and Analysis of Poverty] O13 [Agriculture, Natural Resources, Energy, Environment, Other primary products] Q01 [Sustainable development]

1. Introduction

Energy poverty is a severe development issue in many areas of the globe, especially amongst the poor and vulnerable and in the developing world. The phenomenon is multidimensional and alarming, becoming progressively more so to many extents (Alem and Demeke 2020). Ensuring energy security to all crucially influences one country's development pattern and sustainability outcomes (Groh 2014). As a result, alleviating energy poverty is on the top of the domestic and international development agendas (Sagar 2005). Generally speaking, it is understood that if poor people do not have sufficient access to energy, they will be unable to produce the electricity they need to lift themselves out of poverty and often get proper food, education, health and sanitation, infrastructures and basic daily and development needs (Indrawati 2015).

In spite of its centrality within the energy and development policy debate, energy poverty has not yet reached a univocal definition. Authors have different interpretations of what constitutes energy poverty. However, a standard definition given by the World Economic Forum sees energy poverty as the inaccessibility to environmentally friendly, technologically advanced "energy services and products" (World Economic Forum 2002; Robic et al. 2010).

Families experiencing energy poverty cannot get enough energy services for their homes (Bouzarovski 2014; Fahmy 2011; Buzar 2007). The findings are essential since they demonstrate that disadvantaged populations are at a greater risk of falling into fuel poverty. This vulnerability is often likely to become even a trap (Bouzarovski 2014).

The notion of energy poverty is hugely similar to the concept of fuel poverty and the two concepts are frequently used interchangeably (Li et al. 2014; Bouzarosvski 2014). Even if there are differences, *energy poverty* may be defined as the insufficiency of access to energy services rather than a more general problem relating to the difficulty for families to pay the relevant expenses associated with maintaining a comfortable interior environment (Boardman 2013; V.A. 2009). There are significant measuring problems to address concerning both ideas at the same time. Thompson Snell (2013) provides information on the measurement and estimation of fuel poverty in Europe, whilst Trinomics (2013) discusses the indicators to be used to assess energy poverty (2014).

Energy poverty is a multifaceted conundrum, to be solved with a multidimensional approach (Okushima 2017). According to Gatto and Busato (2020) and Middlemiss Gillard (2014), a connection between energy poverty and energy vulnerability exists. In particular, when there is a shock in the energy price, the aspects of energy vulnerability that may be regarded as concepts in quantitative studies can be ideally identified and quantified (Renner et al. 2019; Busato and Gatto 2019). Even though fuel poverty is directly linked to social disadvantage, there are significant challenges in accurately defining this connection (Fahmy 2011). According to the author, money and energy efficacy (thermal efficiency is a significant predictor) are essential factors determining fuel poverty. At the same time, there are substantial negative health consequences of fuel poverty, particularly for the most vulnerable, such as children (see Liddell and Morris 2010).

In order to assess the overall impact of fuel poverty on a population, it may be necessary to collect extensive data exploring the energy-development nexus and assess it by collection standards (see Gatto et al. 2021). In this regard, energy efficiency is expressly promoted to alleviate fuel poverty (see Sharma et al. 2019 for India and Ismail and Khembo 2015 for South Africa).

In contrast, the notion of "fuel poverty" was thoroughly researched and examined in the United Kingdom and Ireland before being adopted (Walker et al. 2014a; Walker et al. 2014b; Boardman 2013). It was deemed appropriate to alleviate poverty in Northern Ireland by using energy efficiency measures and more particularly an energy-efficient heating system. In the long term, it was feasible to combat fuel poverty by adopting a more proactive approach. Sovacool (2015) explains that the "Warm Front" initiative in England was being implemented, increased energy efficiency during the years 2000-2013 enabled the "fuel poor" to see an improvement in their health conditions.

Energy efficiency can have an impact on the reduction of energy and fuel poverty directly. However, it can also indirectly impact energy and fuel poverty reduction by enhancing and boosting entrepreneurial processes, reducing energy, and fuel poverty by developing new relevant energy-efficient technologies.

At the same time, increased energy efficiency may contribute to greater energy security in this situation if appropriately performed (Selvakkumaran and Limmechokchai 2013). The concepts of energy insecurity and energy security are, in reality, another vital development issue to be considered (see Morrow et al., 2018). While discussing globalization, it is essential to remember that the distribution of energy resources across the globe necessitates a rise in security through time and an increase in insecurity or vulnerability due to energy disparities (Overland 2016). Furthermore, energy insecurity can cause health issues for the general public (Hernandez 2016).

Energy poverty has exhibited its magnitude and harm for short- and long-run development (Guruswamy 2011). To foster sustainable development outcomes, energy poverty requires private-public-third sector cooperation to jumpstart duly initiatives with the scope to tackle energy vulnerability and enhance energy resilience (Gatto and Drago 2021). This translates into sound energy transition strategies and plans (Adom et al. 2021; Bhide &

Monroy 2011). Energy poverty is, indeed, often associated with climate change worsening and increased environmental degradation (Aldieri et al. 2020, 2021; Sovacool et al. 2012; Guruswamy 2011), causing dramatic sustainable development failures or catastrophes.

This work aims to contribute to the growing literature on energy poverty in developing countries and explicitly measure energy poverty, considering it challenging to access various energy sources(as specified by Pachauri and Spreng 2004). It is a recognized fact in the development and sustainability literature that the measurement of energy poverty is an important goal (Siksnelyte-Butkiene et al. 2021; Ozughalu & Ogwumike 2019; Ogwumike et al. 2016; Nussbaumer et al. 2013; Pachauri et al. 2004). However, there is also a problem of arbitrary assumptions to consider when constructing an indicator (see Nussbaumer et al. 2012). In this sense, the interval-based composite indicator is the most appropriate choice to take into account the different assumptions that can be considered for the construction of the same composite indicator and motivates this work's rationale. Indeed, rankings between the different countries as statistical units can be obtained using intervals (particularly assessing the different centers and upper or lower bound).

The article is organized as follows: in section 2, we describe the methodology and the data used; in section 3, we show the results of the work; in section 4, selected policy implications are elicited; finally, in section 5, the conclusions are presented. The appendix section complete this work.

2. Data And Methodology

2.1 Composite indicators

Composite indicators are becoming more and more critical as determining tools for policy analysis. However, they need careful consideration of their construction (Joint Research Centre-European Commission 2008; Freudenberg 2003; Greco et al. 2017; Seth & McGillivray 2018; Hudrliková 2013; Gatto and Drago 2021). Composite indicators may be examined as single aggregate indexes and produce a unique measure; this measure can then be used to compare different statistical units, which can, indeed, be useful for diverse purposes (Joint Research Centre-European Commission 2008; Freudenberg 2003; Gatto and Drago 2021). Another essential feature of composite indicators is their transparency and comparability (Joint Research Centre-European Commission 2008). Therefore, it is essential that these indicators are presented in the same unit of measure and are not susceptible to any biases. Several institutions, agencies, and researchers from different nations have seen significant improvements in the composite indicators they use in recent years. However, statistics agencies are still developing indicators that are more easily understood by the general population. While having a significant impact on the message to communicate, synthetic indicators increase the possibility of criticism due to confident choices' inherent subjectivity (Greco et al. 2019; Drago 2017, 2018 and 2019; Gatto and Drago 2020b and 2021; Seri et al. 2021).

A significant feature of composite indicators is the ability to aggregate and summarize detailed measurements while still giving a broad picture of a particular (complex) phenomenon (Gatto and Drago 2021). Thus, composite indicators are helpful for a variety of reasons. However, the ability to convey the outputs of synthetic indicators and a particular rating to the general public is intuitively regarded as the most valuable feature of this system (Joint Research Centre-European Commission 2008; Saltelli 2007; Freudenberg 2003).

2.2 Data

The article in question is concerned with the construction of a composite indicator of energy poverty via access to electricity (intended as balanced by negative polarity). We use these variables in the construction of the composite indicator as described in Table 1.

Table 1 – Chosen variables

- E.A. Indicator 1: Electrification Planning
- E.A. Indicator 2: Scope of officially approved electrification plan
- E.A. Indicator 3: Framework for grid electrification
- E.A. Indicator 4: Framework for mini-grids
- E.A. Indicator 5: Framework for stand-alone systems
- E.A. Indicator 6: Consumer affordability of electricity
- E.A. Indicator 7: Utility Transparency and Monitoring
- E.A. Indicator 8: Utility Creditworthiness

These variables contribute to the final electricity access score for the Regulatory Indicators for Sustainable Energy (RISE) index and database (RISE 2021, see Banerjee et al. 2017). The rationale was to following the last RISE database, issued in 2020, as the score is a means of support in the attainment of Sustainable Development Goal 7, which asks for "universal access to clean and modern energy" (see also Global Off-Grid Lighting Association 2015). The RISE is a collection of indicators designed to be used to assess policy and "regulatory frameworks that countries have put in place to support the achievement of Sustainable Development Goal 7".

The data considered in our study are related to 2019, the last available year. Therefore, the initial observations are excluded; all these are characterized by missing observation (N\A). In the end, we obtain a dataset based on 54 developing countries as cross-section statistical units, characterized by eight different indicators. Moreover, the different indicators (obtained by the same source, i.e. RISE 2021) are exhaustive of the phenomenon we are investigating because they are jointly at the same part of the scores of the electricity access in the RISE electricity access pillar. Therefore, one can conclude that both indicators are, in fact, a side of the same phenomenon.

2.3 Methodology

This work aims to construct an innovative composite indicator of electricity access to calculate energy poverty. In this respect, we also innovate the methodology because this measure is not based on a single value but an interval of values instead. The advantage of using an interval is that we explicitly have a unique measure of the composite indicator (the center) summarizing and representing a single value for the statistical units considered. However, we also have got an interval representing the variation between a lower bound and an upper bound (Gioia & Lauro 2005; Moore et al. 2009).

Following Gioia and Lauro (2006), an interval $[\overline{x}_i, \underline{x}_i]$ can be considered as:

$$[\overline{x}_i, \underline{x}_i] = \{x / \overline{x}_i \leq x \leq \underline{x}_i\} \quad [1]$$

Tiny intervals, also known as degenerate intervals of the type $[\overline{x}_i, \overline{x}_i]$ are equal to real numbers (Gioia & Lauro 2005, 2006; Moore et al. 2009). Classical composite indicators can be seen as degenerate intervals where the relevant problem is the assumptions (weightings, the selection of the indicators to include) on which the construction of the composite indicator is based, which are to a certain extent subjective (Freudenberg 2003; Greco et al. 2019).

It does not help to construct an interval considering two or three different versions of the composite indicator based on different approaches. Here we are exploiting a continuum of different observations belonging to an interval.[1] These types of composite indicators have rapidly growing in literature.

We start from the standardization of the single indicators (Joint Research Centre-European Commission 2008; Freudenberg 2003; Gatto and Drago 2021):

$$I^t_{qc} = \frac{x^t_{qc} - x^t_{qc=\overline{c}}}{\sigma^t_{qc=\overline{c}}} \quad [2]$$

Here x^t_{qc} identify the variable q considered at a specific point t in time

$x^t_{qc=\overline{c}}$ is the mean for the considered variable and $\sigma^t_{qc=\overline{c}}$ is the standard deviation

In order to construct the composite indicator, we identify all the variables as components. Then, the various indicators have been standardized to achieve the same scale for all indicators in use. When indications are converted to a common scale having a zero mean and a standard deviation of one, this is referred to as standardization or z-scores.[2]

Then, to calculate the final composite indicator, the sorting components are combined by aggregating the different values. In this sense, we compute the composite indicators facing the existing uncertainties on constructing the composite indicators making use of interval data. The advantage of using an interval is that we have not been forced to adopt a unique specification for constructing our composite indicator. However, we can consider different assumptions and specifications (we have, indeed, not forced to either adopt an equal weighting specification). The final result is an interval $I[x]_i$ of the different composite indicators obtained. Following Lauro and Palumbo (2000) and Moore et al. (2009), we can also calculate some parameterizations of our interval, allowing a comparison between the different intervals. In this way:

$$x_i^c = \frac{1}{2}(\overline{x_i} + x_i)\text{[3]}$$

Where x_i is the upper bound of the interval and the $\underline{x_i}$ is the lower bound.

The center x_i^c is a measure that allows summarizing the most plausible value obtained by the interval. Finally, a measure of the variability is the radius, which has the same value considering the two different radii: the radius that departs from the lower bound to the center and the radius that departs from the center and goes to the upper bound.

So the radii x_i^r are:

$$x_i^r = \frac{1}{2}(\overline{x_i} - x_i)\text{[4]}$$

A third measure that can be computed can be the interval range x_i^{rn}, which is simply obtained by summing the two radii or subtracting from the upper bound the lower bound:

$$x_i^{rn} = (\overline{x_i} - \underline{x_i})\text{[5]}$$

Different rankings can be obtained by considering the center of the intervals (equivalent to rank classical composite indicators, which can be considered tiny intervals). However, it is also possible to rank the radii differently and upper and lower bound (see Mballo and Diday 2005; Song et al. 2012).

This procedure allows internalizing the sensitivity analysis, a relevant phase of constructing a classic composite indicator (Saisana et al. 2005; Saltelli et al. 2008). In this respect, the interval data allows measuring the variability induced by using different assumptions on the construction of the composite indicator. In this case, the interval equally considers all different results due to the different assumptions (for instance, weightings), and we can observe an increase of the radii of the interval-based composite indicator.

More explicitly, following Gatto and Drago (2021), we can obtain the different composite indicators, which are helpful to explore the space of the results of the original composite indicator considering the different assumptions (in our case, the weighting schemes) we vary. So we consider a Monte-Carlo simulation in which we can obtain different scenarios for our composite indicator. In this sense, we can make use of different assumptions as different weighting schemes. So following Gatto and Drago (2021, 2020b) and Drago (2017), we get four different phases on the construction of an interval-based composite indicator:

1. A uniform distribution on the Monte-Carlo simulation we are performing allows computing every single weight. In this respect, we simulate a new preliminary weight for each component, which is not necessarily

equal to the component's final weights. So considering the simulation, the equal weighting is a plausible case but we also cover situations in which some components can be weighted more than others.

2. The composite indicator's preliminary weights should be added together to provide a value representing a theoretical total. Therefore, the various candidate weights are added together, and then each one is divided for the sum of the weighting scheme obtained to obtain the final weight for each of the eight components considered. Thus, the result comprehends a single weight for the components of the composite indicators.
3. We repeat the procedure 100000 times, and for each simulation, we obtain repeating the procedure above a single (probabilistically different) weighting scheme. Hence, in the end, we obtain 100000 weighting schemes which are the baseline in the construction of the composite indicator based on an interval.
4. Finally, we compute the parameters of the composite indicators considering the center, the radii, and the range.

From the diverse centers and radii, we can construct the different rankings. Then, to perform a sensitivity analysis of the different results, we compute a triplex representation based on less intense assumptions (on the triplex representations see Williamson 1989; Drago 2021 on the context of the interval-based composite indicators). In this case, the sensitivity analysis is different from the classic one because we have already considered the different assumptions in our indicator, and now we compare different representations.

A triplex representation of the interval can be defined in this way: $[\underline{x}, \tilde{x}, \overline{x}]$ where the $\tilde{x}$ corresponds to the equal weighting scenario. However, it is essential to note that the radii are not symmetric but can be different. This fact is significant in interpreting the results of the analysis in which the triplex representation is involved.

The triplex representation is used to represent the intervals the quantiles 0.95 and 0.05, excluding the observations lying outside these intervals. In this respect, we are using some more reasonable intervals that exclude some extreme scenarios (namely, some weighting schemes that are particularly favorable for a country or particularly adverse). The center of the interval on the triplex representation is based on the equal weighting scenario. Therefore, it is helpful to compare the results obtained by the center of the interval with the equal weight scenario. Furthermore, the triplex representation can be used as a sensitivity analysis to compare the results obtained with the interval composite indicators with different assumptions. In order to compare these different assumptions, we subtract the triplex representation from the interval.[3] So we have two generic intervals:

$$I[x]_i - I[x]_{i'} = I[X] \equiv \left[\left(\underline{x_i} - \overline{x_{i'}}\right), \left(\overline{x_i} - \underline{x_{i'}}\right)\right] \qquad [6]$$

In this way, we elicit the relevance of the extreme scenarios. It is noticeable that the higher the difference between the two intervals, the more relevant the possibility for extreme scenarios. In this sense, the results are an interval and represent the relevance of possible extreme scenarios in the interval analysis. So, this means that to analyze policies and evaluate vulnerability (the difference between lower limits) and resilience for each nation, the findings are critical (that is the difference between the upper bounds).

[1] For the interval data and the statistical techniques in which they can lie, see Gioia and Lauro 2005, for the interval-based composite indicators and the methodologies to construct and analyze them see Drago (2017, 2018, 2019), Drago & Gatto (2018); Drago & Ricciuti (2018); Mazziotta and Pareto (2020); Seri et al. (2021) and also with applications to energy, Gatto and Drago (2020b and 2021).

[2] About a review of the procedures in the construction of the composite indicators, see Joint Research Centre-European Commission 2008.

[3] For the algebra of the interval and particularly for the subtraction Lauro and Palumbo (2000) Moore et al. (1979).

3. Results

It is possible at this point to interpret the different tables and results. From Table 2, we can analyze the interval-based composite indicator ranking by the center. The center is the most representative value for the intervals considered. We can observe that Guatemala reaches the first position, followed by Bangladesh, Tanzania, Cambodia, Ethiopia, South Africa and Kenya.

Two cases are emblematic in this group of countries: Bangladesh and Tanzania (the first two countries in the ranking). According to Ichord (2019), Bangladesh is a "leader" in developing emerging nations, has been the first among developing countries to expand access to electricity. According to estimates, electricity availability in Bangladesh has grown "from 55 percent in 2010 to 88 percent in 2017" (Ichord 2019), which were at the same tune rural regions accounting for 81 percent of the total.

Aiming to attain 100 percent coverage by 2021, the government of Bangladesh is attempting to accomplish this ambitious goal. However, the internal inability to provide consistent electricity has hampered growth (Ichord 2019). It shall be remarked that, according to the World Bank (2016), Tanzania's socioeconomic development goals will be impossible to attain without cheap and reliable energy. Given that just 36 percent of households have access to power, the World Bank is aiding the government with a project to increase access to cheap, efficient, and modern energy while safeguarding the sector's long-term operational and financial viability and sustainability (World Bank 2016).

South Sudan, the Congo Republic, and Somalia perform the worst (last, penultimate and third last, respectively). The bad practice of South Sudan is emblematic because, considering the 12.5 million inhabitants in South Sudan, only 1percent have the accessibility to the electric grid (Gallucci 2020). However, after years of civil strife, the nascent nation of East-Central Africa is reviving its electrical industry. As a result, South Sudan is on the verge of building its power grid (Gallucci 2020; Hundermark 2021).

Table 3 and Table 6 in the Appendix show information based on another relevant interval parameter: the radius (or radii because there are two). The radius is a way to represent the variability of the interval-based composite indicator. Here, Chad, Solomon Islands, Nepal, Zambia, and Afghanistan get the best positions. A lower variability pertains to Niger, the Philippines, Yemen, the Congo Republic and Bangladesh. In this respect, these countries show the highest level of robustness and a lower vulnerability for a single indicator. The results can be compared with a similar weighting scenario (Table 4), showing, on one hand, the robustness of the results obtained and on the other hand some relevant differences. Bangladesh is not the first country on the ranking, the best score is achieved by Tanzania.

There are, at the same time, differences between the other positions on the ranking. This result shows the consistency of the result obtained examining the center of the interval. The radii represent a new contribution that allows discovering essential differences between the different countries. In particular, countries that are fairly robust, such as Yemen, the Philippines and Niger, also show a lower variance considering the different initial components and simultaneously very low radii. Countries such as Chad, the Solomon Islands and Nepal show a higher vulnerability because the variance of the different components of the interval-based composite indicator is higher than the international average level. Nevertheless, at the same time, these countries show a higher radius. That means they can improve their rank, but conversely, they are at risk because the different situation of the whole number of the indicator shows essential weaknesses. So in this respect, the situation should be carefully considered.

Then we can compute the triplex representation (Table 7 in the Appendix), which allows us to observe a different type of representation. In this case, we consider two different smoother upper and lower bound with respect to the original interval computed. So the results should be based on less extreme scenarios. The difference between the two representations computed using interval algebra is obtained in Table 5. The differences between the two extremes (the lower bound and the upper bound) obtained by the difference of the two intervals represented (Table 6 and Table 7) represent the capacity for a single country to have a specific path in the case of the upper bound to improve their position. That means a possibility to improve their situation and position considering the composite indicators computed exists. This indicator can be considered a signal of resilience.

Conversely, the lower bound represents the vulnerability to situations where a combination leads to the worst scenarios. This fact could be a signal of extreme vulnerability, instead. Countries that show relevant possibility to increase their positions, considering extreme optimistic scenarios, are Chad and Afghanistan. These regions can have straightforward directions to improve their electricity access situation. At the same time, Chad, Nigeria and Rwanda show relevant problems of energy poverty vulnerability. Considering the worst scenario of the interval considered concerning the triplex representation (based on the 0.05 quantile and not on the minimum), we can observe that in the case of extreme scenario, these three countries show very relevant reductions in the value of electricity access.

4. Policy Implications

The approach presented in this work allows identifying the situations showing higher resilience and vulnerability at an international level. So in this respect, we can use this approach to evaluate situations highlighting some virtuous or vicious paths to a relevant improvement or worsening in domestic performance which may be of interest for energy and development policy. The latter may be used as alerters which may trigger in case of cautious situations. The outcomes may also be interpreted as indicators of energy resilience or vulnerability. In both cases, the computed index may return relevant development policy recommendations to be used for energy poverty assessment.

Considering all the different rankings obtained, we can evaluate and classify different situations and policy implications. The rankings assessing the center (or the classical assumption of "equal weighting", able to respond to the same question the center answer) is a general value of electricity access can be obtained examining the multitude of the scenario considered. So the center's ranking allows evaluating the general level of electricity access at the international level. More interesting and innovative are the other rankings. The radii show beneficial information, which can improve or worsen the situation on the basis of different assumptions. Enormous radii can improve or worsen the situation depending on the distribution of numbers on the various indicators. Enormous radii can be due to a higher upper bound or a lower upper bound respect other extremes at the international level.

That means, more specifically, an intense vulnerability shall exist and on the other side, a possibility to strongly improve the situation considering in policies the indicators showing relevant performances at an international level. Therefore, to improve their position, these countries should take into account these components as foundations for their energy and development policies. Moreover, countries can improve their status by examining the weakness points based on other components disparity between the lower bound of the intervals represented by the composite indicator. The triplex representation identifies another signal of vulnerability.

The interval resulting from the subtraction on their lower bound shows a vulnerability due to extreme scenarios. The countries falling in this situation should avoid these extreme scenarios because the composite indicator results can be significantly worse than most scenarios. Differently, the countries which improve enormously the interval based on the difference of the two other intervals (the composite indicator and the triplex representation) show relevant paths to growth in light of some scenarios. These scenarios are possibly too extreme to be evaluated in practice as economic or sustainable development policies. This result shows the need, aside from, to consider the indicators which a country shows most decisive point and a strategy to improve weaknesses. So in this sense, there is a need to eradicate vulnerability in terms of electricity access to avoid falling into traps.

5. Conclusions

This work had the mission to shed light on energy poverty by improving our understanding in terms of energy and development policy. To this end, an interval-based composite indicator on 54 developing countries, representative of the totality of the world regions has been built. Additional tests and sensitivity analyses complete the inquiry. We learnt a number of facts on the domestic energy poverty situations of the selected countries, whereby we can distinguish energy resilient and energy vulnerable countries. The explored issues returned insightful guidance to be examined for achieving sustainable development goals (SDGs).

Poor access to energy is a significant problem in many parts of the world, particularly amongst the vulnerable socioeconomic groups and those living in developing countries. The World Economic Forum conceives energy poverty as the inability to get environmentally friendly, technologically sophisticated "energy services and goods". Therefore, it is possible to define energy poverty as a lack of adequate access to energy services rather than a more general issue related to the inability of families to pay the necessary costs involved with maintaining a pleasant interior environment.

Associated energy and development policy issues have to be highlighted. Before being implemented in the United Kingdom and Ireland, the idea of "fuel poverty" was extensively studied and evaluated in both countries. Energy efficiency has the potential to have a direct effect on the alleviation of energy and fuel poverty. While this will directly contribute to the decrease, it will also have an indirect effect by improving and promoting entrepreneurial activities, which will, in turn, contribute to the creation of new applicable energy-efficient technology.

In this study, we have approached energy poverty by measuring electricity access using a new approach based on an interval-based composite indicator. In this respect, we can consider two different representations. Based on the random Monte-Carlo simulations which rely on the different assumptions of the composite indicators (for instance, different weightings), the first one allows constructing the intervals and relative parameterizations. From the parameterizations, we can construct the different rankings. At the same time, from the difference between the two intervals (interval-composite indicators based on the extreme and the triplex representation based on the 0.05 and 0.95 quantiles and also on the equal weighting scenario), we can identify the different countries performing highly or on the worst way in the scenarios.

These results can unveil significant energy and development policy lessons because they can show a higher level of domestic resilience or vulnerability. At the same time, these tools can, nevertheless, be positive if the difference is higher between the upper bound of the interval respect the other one of the triplex representation. Where the difference is higher is possible to observe a higher resilience for the considered country.

The presented work is not exempt from limitations. Electricity access has been used as a proxy of energy poverty. However, this theoretical choice has been interpreted to be more solid with respect to subjective interpretations. On top of that, this option returns more extensive and reliable data. Further research can consider an exploration of fuel poverty. Another important topic to examine in the future is the difference between the notions of energy insecurity and energy security.

Appendix A

Table 2 – Interval-based composite indicator: ranking by the center

	Center
Guatemala	0.97
Bangladesh	0.92
Tanzania	0.88
Cambodia	0.85
Philippines	0.85
Ethiopia	0.84
South Africa	0.82
Kenya	0.81
Uganda	0.67
Cameroon	0.62
Rwanda	0.55
India	0.55
Nepal	0.53
Nigeria	0.52
Benin	0.44
Niger	0.41
Indonesia	0.4
Nicaragua	0.36
Togo	0.33
Ghana	0.33
Myanmar	0.31
Angola	0.3
Côte d'Ivoire	0.23
Malawi	0.22
Sudan	0.21
Zambia	0.2
Burkina Faso	0.16
Zimbabwe	0.11
Lao PDR	0.07
Pakistan	0
Haiti	-0.02
Afghanistan	-0.07
Senegal	-0.07
Vanuatu	-0.11
Honduras	-0.14
Papua New Guinea	-0.23
Solomon Islands	-0.33
Liberia	-0.37
Mozambique	-0.38
Guinea	-0.43
Burundi	-0.45
Sierra Leone	-0.49
Madagascar	-0.54
Mauritania	-0.61
Congo, Dem. Rep.	-0.68
Mali	-0.8
Chad	-0.9
Mongolia	-0.91
Eritrea	-1.05
Yemen, Rep.	-1.06
Central African Republic	-1.1
Somalia	-1.19

Congo, Rep.	-1.21
South Sudan	-1.49

Table 3 – Interval-based composite indicator: ranking by radii

	Radii
Chad	1.45
Solomon Islands	1.18
Nepal	0.98
Zambia	0.93
Afghanistan	0.92
Malawi	0.9
Rwanda	0.9
Haiti	0.86
Cambodia	0.84
Côte d'Ivoire	0.84
Madagascar	0.8
Myanmar	0.79
Zimbabwe	0.78
Guinea	0.78
Nigeria	0.77
Pakistan	0.76
Congo, Dem. Rep.	0.74
Togo	0.74
Eritrea	0.74
Vanuatu	0.73
Honduras	0.73
Angola	0.71
Nicaragua	0.7
Burundi	0.69
Indonesia	0.66
Mauritania	0.66
Sudan	0.64
Tanzania	0.61
Ghana	0.61
Kenya	0.6
Sierra Leone	0.58
Ethiopia	0.58
Liberia	0.58
Papua New Guinea	0.57
Mali	0.54
Benin	0.52
Mozambique	0.51
Lao PDR	0.51
Central African Republic	0.5
Cameroon	0.48
Guatemala	0.48
Senegal	0.45
South Africa	0.44
India	0.44
Somalia	0.41
Mongolia	0.41
South Sudan	0.4
Burkina Faso	0.39
Bangladesh	0.38
Uganda	0.36
Congo, Rep.	0.34
Yemen, Rep.	0.3

Philippines	0.29
Niger	0.25

Table 4 – Equal weighting scenario

	Equal weighting
Tanzania	0.98
Bangladesh	0.97
Philippines	0.92
South Africa	0.89
Guatemala	0.88
Ethiopia	0.86
Cambodia	0.84
Kenya	0.84
Nigeria	0.71
Rwanda	0.7
Uganda	0.7
India	0.63
Cameroon	0.62
Benin	0.6
Nicaragua	0.49
Nepal	0.45
Myanmar	0.44
Niger	0.4
Ghana	0.38
Angola	0.37
Indonesia	0.37
Togo	0.35
Côte d'Ivoire	0.32
Malawi	0.29
Zambia	0.17
Burkina Faso	0.16
Sudan	0.15
Zimbabwe	0.15
Lao PDR	0.05
Pakistan	-0.03
Vanuatu	-0.05
Haiti	-0.07
Honduras	-0.14
Papua New Guinea	-0.23
Senegal	-0.23
Afghanistan	-0.26
Guinea	-0.33
Liberia	-0.46
Mozambique	-0.5
Burundi	-0.55
Sierra Leone	-0.56
Madagascar	-0.6
Solomon Islands	-0.61
Congo, Dem. Rep.	-0.69
Mauritania	-0.72
Mali	-0.85
Eritrea	-0.92
Mongolia	-0.97
Chad	-1
Central African Republic	-1.02
Yemen, Rep.	-1.1
Somalia	-1.11

Congo, Rep.	-1.19
South Sudan	-1.51

Table 5 – Difference between the interval-based composite indicator and triplex representation

	diff_min	diff_max
Afghanistan	-0.37	0.7
Angola	-0.54	0.4
Bangladesh	-0.3	0.2
Benin	-0.5	0.2
Burkina Faso	-0.25	0.24
Burundi	-0.34	0.5
Cambodia	-0.54	0.54
Cameroon	-0.32	0.3
Central African Republic	-0.36	0.23
Chad	-0.87	1.07
Congo, Dem. Rep.	-0.46	0.49
Congo, Rep.	-0.23	0.2
Côte d'Ivoire	-0.63	0.44
Eritrea	-0.58	0.37
Ethiopia	-0.39	0.35
Ghana	-0.44	0.34
Guatemala	-0.21	0.35
Guinea	-0.63	0.44
Haiti	-0.49	0.61
Honduras	-0.44	0.45
India	-0.35	0.21
Indonesia	-0.39	0.43
Kenya	-0.4	0.36
Lao PDR	-0.31	0.35
Liberia	-0.26	0.46
Madagascar	-0.46	0.56
Malawi	-0.6	0.5
Mali	-0.3	0.38
Mauritania	-0.32	0.52
Mongolia	-0.2	0.29
Mozambique	-0.23	0.44
Myanmar	-0.59	0.37
Nepal	-0.52	0.63
Nicaragua	-0.52	0.32
Niger	-0.13	0.17
Nigeria	-0.65	0.3
Pakistan	-0.44	0.46
Papua New Guinea	-0.33	0.36
Philippines	-0.25	0.11
Rwanda	-0.65	0.41
Senegal	-0.13	0.43
Sierra Leone	-0.25	0.42
Solomon Islands	-0.49	1.02
Somalia	-0.32	0.2
South Africa	-0.34	0.17
South Sudan	-0.22	0.25
Sudan	-0.34	0.42
Tanzania	-0.45	0.29
Togo	-0.47	0.37
Uganda	-0.26	0.21
Vanuatu	-0.51	0.41
Yemen, Rep.	-0.16	0.24

Zambia	-0.59	0.62
Zimbabwe	-0.55	0.46

Table 6 – Interval-based composite indicator

	center	radii	min	max
Afghanistan	-0.07	0.92	-0.99	0.85
Angola	0.3	0.71	-0.41	1.01
Bangladesh	0.92	0.38	0.54	1.3
Benin	0.44	0.52	-0.08	0.96
Burkina Faso	0.16	0.39	-0.23	0.55
Burundi	-0.45	0.69	-1.14	0.24
Cambodia	0.85	0.84	0.01	1.69
Cameroon	0.62	0.48	0.14	1.1
Central African Republic	-1.1	0.5	-1.59	-0.6
Chad	-0.9	1.45	-2.35	0.55
Congo, Dem. Rep.	-0.68	0.74	-1.43	0.06
Congo, Rep.	-1.21	0.34	-1.55	-0.86
Côte d'Ivoire	0.23	0.84	-0.61	1.07
Eritrea	-1.05	0.74	-1.79	-0.31
Ethiopia	0.84	0.58	0.27	1.42
Ghana	0.33	0.61	-0.28	0.93
Guatemala	0.97	0.48	0.49	1.45
Guinea	-0.43	0.78	-1.22	0.35
Haiti	-0.02	0.86	-0.88	0.84
Honduras	-0.14	0.73	-0.87	0.58
India	0.55	0.44	0.11	0.99
Indonesia	0.4	0.66	-0.25	1.06
Kenya	0.81	0.6	0.22	1.41
Lao PDR	0.07	0.51	-0.44	0.57
Liberia	-0.37	0.58	-0.95	0.2
Madagascar	-0.54	0.8	-1.34	0.25
Malawi	0.22	0.9	-0.69	1.12
Mali	-0.8	0.54	-1.34	-0.25
Mauritania	-0.61	0.66	-1.26	0.05
Mongolia	-0.91	0.41	-1.32	-0.51
Mozambique	-0.38	0.51	-0.9	0.13
Myanmar	0.31	0.79	-0.48	1.09
Nepal	0.53	0.98	-0.44	1.51
Nicaragua	0.36	0.7	-0.34	1.07
Niger	0.41	0.25	0.16	0.66
Nigeria	0.52	0.77	-0.25	1.28
Pakistan	0	0.76	-0.76	0.76
Papua New Guinea	-0.23	0.57	-0.79	0.34
Philippines	0.85	0.29	0.55	1.14
Rwanda	0.55	0.9	-0.34	1.45
Senegal	-0.07	0.45	-0.52	0.38
Sierra Leone	-0.49	0.58	-1.07	0.09
Solomon Islands	-0.33	1.18	-1.51	0.85
Somalia	-1.19	0.41	-1.6	-0.77
South Africa	0.82	0.44	0.38	1.26
South Sudan	-1.49	0.4	-1.88	-1.09
Sudan	0.21	0.64	-0.44	0.85
Tanzania	0.88	0.61	0.27	1.5
Togo	0.33	0.74	-0.4	1.07
Uganda	0.67	0.36	0.3	1.03
Vanuatu	-0.11	0.73	-0.84	0.62
Yemen, Rep.	-1.06	0.3	-1.36	-0.75

Zambia	0.2	0.93	-0.73	1.13
Zimbabwe	0.11	0.78	-0.67	0.89

Table 7 – Triplex Representation

	min	max	equal
Afghanistan	-0.61	0.14	-0.26
Angola	0.13	0.6	0.37
Bangladesh	0.84	1.1	0.97
Benin	0.42	0.77	0.6
Burkina Faso	0.03	0.32	0.16
Burundi	-0.8	-0.26	-0.55
Cambodia	0.55	1.15	0.84
Cameroon	0.45	0.8	0.62
Central African Republic	-1.23	-0.83	-1.02
Chad	-1.47	-0.52	-1
Congo, Dem. Rep.	-0.96	-0.44	-0.69
Congo, Rep.	-1.32	-1.06	-1.19
Côte d'Ivoire	0.02	0.62	0.32
Eritrea	-1.21	-0.68	-0.92
Ethiopia	0.66	1.07	0.86
Ghana	0.16	0.59	0.38
Guatemala	0.7	1.09	0.88
Guinea	-0.59	-0.09	-0.33
Haiti	-0.39	0.23	-0.07
Honduras	-0.43	0.13	-0.14
India	0.46	0.78	0.63
Indonesia	0.14	0.64	0.37
Kenya	0.62	1.05	0.84
Lao PDR	-0.13	0.23	0.05
Liberia	-0.69	-0.26	-0.46
Madagascar	-0.88	-0.31	-0.6
Malawi	-0.09	0.62	0.29
Mali	-1.03	-0.63	-0.85
Mauritania	-0.94	-0.47	-0.72
Mongolia	-1.11	-0.8	-0.97
Mozambique	-0.67	-0.31	-0.5
Myanmar	0.11	0.72	0.44
Nepal	0.07	0.88	0.45
Nicaragua	0.18	0.75	0.49
Niger	0.29	0.49	0.4
Nigeria	0.41	0.99	0.71
Pakistan	-0.32	0.3	-0.03
Papua New Guinea	-0.46	-0.02	-0.23
Philippines	0.8	1.03	0.92
Rwanda	0.31	1.04	0.7
Senegal	-0.4	-0.05	-0.23
Sierra Leone	-0.83	-0.33	-0.56
Solomon Islands	-1.02	-0.18	-0.61
Somalia	-1.28	-0.97	-1.11
South Africa	0.72	1.09	0.89
South Sudan	-1.66	-1.34	-1.51
Sudan	-0.1	0.43	0.15
Tanzania	0.72	1.2	0.98
Togo	0.06	0.7	0.35
Uganda	0.57	0.82	0.7
Vanuatu	-0.33	0.21	-0.05
Yemen, Rep.	-1.2	-0.99	-1.1

Zambia	-0.14	0.51	0.17
Zimbabwe	-0.12	0.44	0.15

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