INTRODUCTION

Sustainable economic prosperity has become a major policy initiative for economies worldwide. To accomplish this objective, it is imperative to reduce CO₂ emissions, which makes attaining sustainable development goals problematic. In this regard, improving economic growth without disastrously hampering the environment is a key factor in the fight against climate change. As such, many nations and multinational organizations have promulgated laudable and sound policy initiatives to achieve CO₂ emission reduction targets. One such policy directive is the reduction of CO₂ emission drastically by the end of the 21st century formulated by the intergovernmental panel on climate change (IPCC) in 1996.¹
As environmental topics have become important and attracted global attention, many nations are being required to adequately study, investigate, and publish needed information about their policy effects. To some extent, developed nations have made huge progress in this regard but little progress has been made in the Africa sub-region.

Energy efficiency measurement plays a critical role in ensuring the balance between energy demand and environment pollution. Energy efficiency estimations generally help in the reduction of related greenhouse gas emissions. Energy efficiency improvement is essential to environmental sustainability, industries, and the accomplishment of the “sustainable energy for all” initiative.

In Africa, the policy awareness of energy efficiency improvement has been generally encouraging but a lot more is still expected. The “sustainable energy for all” initiative was launched in 2011 by the UN secretary-general, with the view to promoting energy efficiency improvement worldwide. In 2013, the Africa Development Bank demonstrated promising strides toward the implementation of the policy in Africa. Also, the Chinese government announced the implementation of the “One Belt One Road Initiative (BRI)” program in 2013 to facilitate international trade as well as infrastructure development linking Asia-Europe-Africa. Among other things, the program seeks to promote energy efficiency cooperation and the supply of clean energy among countries within the BRI. Apart from the regional level policies, there are a lot of country-level specific initiatives being implemented to help enhance energy efficiency. To fully understand the channels for energy efficiency improvement, energy efficiency measurement and assessment is paramount. However, literature on energy efficiency using DEA approach from the African perspective is relatively scanty.

Empirically, the nonparametric- and parametric-based techniques have been employed to measure efficiency worldwide. In Africa, however, the parametric approach in the form of stochastic frontier analysis is commonly used to estimate energy efficiency. However, energy efficiency studies that apply the nonparametric approach appear to relatively scanty in Africa. This study tries to investigate the dynamic implications of carryover factors as part of the energy evaluation processes in Africa. However, traditional efficiency measurement only focuses on the production of desirable output, while neglecting the dynamic impact of environmentally undesirable factors of production.

Data Envelopment Analysis (DEA), as formulated by Charnes et al., has been widely applied in the energy and environmental efficiency (EEE) analysis. The said methodological framework can easily handle many input-many output phenomena. However, the traditional DEA models are always constructed to measure the technical efficiency of the investigated decision-making units (DMUs) statically. Therefore, several biased efficiency estimates are normally obtained should we employ only static optimization. This is because CO₂ emissions as an undesirable output factor is usually not incorporated into the model but only GDP is always included as a good output in the estimated DEA model. Specifically, GDP is always considered the original output factor “the more the better” while, CO₂ emissions are normally deployed as a bad output factor “the less the better.” Recently, there has been a plethora of new methodologies formulated for the measurement of DMUs with the inclusion of undesirable output factors in the estimated DEA model. Tyteca proposed that bad output factors should be treated as an input in DEA modeling, whereas Ramanathan deployed CO₂ emissions in their reciprocal form in the evaluation of the nexus between economic growth and energy consumption for the Middle East and North Africa countries.

To adequately estimate the efficiency with the DEA modeling approaches incorporating good and bad output factors simultaneously, some researchers have proposed several DEA models based on the perspective of environmental DEA technology. A comprehensive review of these new methods and their areas of application are presented by. The slack-based measure (SBM) DEA model formulated by Tone appears to be the most frequently used compared with the other models proposed. In this study, we adopted Tone and Zhou et al. SBM-DEA modeling technique where more of the good output, less of the bad outputs, and fewer inputs factors are described as efficient. Thus, the SBM-DEA model is very robust in the evaluation of environmental efficiency. From the extended literature, Zhou evaluated the relative CO₂ emissions efficiency among OECD economies from 1998 to 2012, employing the SBM method. Hu and Kao studied the energy-saving efficiency for a sampled Asia-Pacific Economic Cooperation (APEC) economies between the period of 1991 to 2000 using the SBM model methodology. Choi et al. investigated the energy efficiency abatement cost in China utilizing the SBM approach by incorporating CO₂ emission as a bad output. Li et introduced an extended version of the SBM model to systematically measure environmental efficiency from the period of 1991 to 2010. Besides energy efficiency, the SBM methodological framework was also used to exploit the efficiency in the banking industry, industry efficiency, and educational efficiency.

Furthermore, in the available literature, some researchers employed the dynamic DEA modeling technique for measuring the dynamic nature of DMUs over two consecutive periods. Sengupta and Färe and Grosskopf are regarded as pioneers in the formulation of the dynamic modeling approach. In a study by Sengupta, the model was constructed on cost adjustment method, where he introduced quasi-fixed inputs and their feasible paths in the estimated model. Alternatively, Färe and Grosskopf proposed a multi-output production model by including multi-periods in their study. Since then, other meaningful DEA models have been
proposed. Tone and Tsutsui proposed a new SBM model with the incorporation of crossover variables, which can measure relative efficiency considering two consecutive periods. Jafarian-Moghaddam and Ghoseiri extended the dynamic DEA model to incorporate fuzzy multi-objective frontiers, to systematically study the relative efficiency of the railways. Sueyoshi investigated the relative efficiency of coal-fired power-producing plants in the United States (US) by employing the dynamic DEA window methodology. They proposed that the US should consider the inclusion of CO₂ emissions reduction strategies into the Clean Air Act (CAA) to reduce emissions.

With the upsurge of global warming concerns, issues relating to energy consumption and the environment have attracted the attention of scholars worldwide, to finding the trade-off between sustainable economic prosperity and environmental protection. On those bases, Färe et al. developed the Malmquist DEA model to adequately estimate both efficiency and technical changes sub-component of production units. In DEA energy efficiency studies, there are two established ways of handling undesirable output factors in the DEA model: First, the weak disposability (WD) assumption states that undesirable factors are used in their original form and the second, strongly disposable (SD) where undesirable factors are treated in their various translation methods such as the reciprocals or additive inverses forms before applications.

In other jurisdictions, energy efficiency studies that applied the DEA modeling techniques are omnipresent, for instance, in US; in APEC economies; in China; OECD economies; Japan; and in India. Among the African economies, there exists a research gap relative to the above-mentioned prior studies, which were conducted in developed, Asian countries and high-income countries where the context is completely different, although there are some important energy efficiency studies carried out in Africa. Moreover, despite their contributions—those studies do not consider the dynamic implications of undesirable output (CO₂ emissions) and carryover factors effect over time. The projection/adjustment analysis of the slack was also ignored in those studies.

Again, due to CO₂ emission concerns, Guo et al. estimated the dynamic energy performance of selected OECD nations from 2000 to 2010 by adopting the dynamic SBM approach with the inclusion of CO₂ emissions as a bad output. Also, Lu and Lu assessed the dynamic energy efficiency of 28 sample European Union nations during the period 2009 to 2013. They deployed only GDP as the carryover factor and CO₂ emissions as an undesirable output. Furthermore, Lu et al. investigated the dynamic energy efficiency among 48 selected high-income economies by incorporating CO₂ emissions as a bad output from 2010 to 2014. The vast majority of the above studies are from developed and Asian economies, but little has been done in the African economies' perspective. This study, therefore, aims to apply the dynamic slack-based measure (SBM) DEA model to measure energy efficiency in Africa taking into account both undesirable and carryover factors in the production technology. One advantage of the dynamic DEA model over the static one is that it can adequately help researchers understand relative efficiency change over time.

This study contributes to the energy efficiency literature in the following strands: (a) It provides the first Africa estimation of energy efficiency considering the dynamic implications of carryover factors in the energy production technology; (b) the dynamic SBM-DEA model adequately helps in revealing the potential areas of operational inefficiency among the selected African countries; (c) the study assume energy stock as the dynamic linking factors connecting the two consecutive time periods while CO₂ emission is used as bad output factor. This study is the first to employ energy stock in evaluating energy efficiency in Africa. (d) The study provides projection or adjustment analysis for the inefficient African countries based on the inputs, outputs, and carryover factor. Empirically, the study also contributes by conducting energy efficiency analysis in Africa. Finally, energy efficiency improvement mechanisms are proposed and discussed based on the empirical results.

The rest of the study is organized as follows. The study dynamic SBM-DEA model is presented in the “Materials and Methods” section. The study empirical results are in Section 3. The conclusions and policy implications of the study are displayed in Section 4.

## 2 | MATERIALS AND METHODS

### 2.1 | Dynamic SBM model

Evaluating energy efficiency with dynamic DEA approach is essential. This is because it affords scholars the opportunity to understand performance changing over time. In Africa, strategic energy efficiency improvement and investment are great distress for economic prosperity. Again, failure to account for the dynamic nature (crossover factors activities) and bad output factors normally leads to an overestimation of the efficiency estimates. This makes it essential to undertake a dynamic analysis in the presence of data availability. In this regard, Tone and Tsutsui formulated a new dynamic SBM model integrating crossover factors. This study selected the nonoriented DSBM model by Tone and Tsutsui since it can easily handle the inputs, outputs, and crossover factor individually. This means that the DSBM model can allocate the weights to each understudy variable regardless of their degree of position. Interestingly, Tone and Tsutsui adequately proposed that dynamic DEA models have four types of correlation variables (i.e., fixed, free, good, and bad) in a consecutive period’s framework system. Therefore, energy
stock was employed as the linking variables. The selection of energy stock depicting the profit factor that connects the two consecutive production years. The central aim of this study is that African economies must take pragmatic steps toward improving energy efficiency as well as CO₂ emission reduction.

This study assumes that there are \( n \) nations in Africa to be systematically analyzed. For the \( j \)-th nation, \( j = 1, \ldots, n \) across two consecutive periods \( (t = 1, \ldots, T) \), where \( m \) inputs \((i = 1, k, m)\) are consumed by each investigated DMU. \( F \) denotes nondiscretionary (fixed) inputs \((i = 1, k, m)\); \( S \) is the output \((i = 1, k, s)\); \( P \) represents nondiscretionary (fixed) outputs \((i = 1, k, r)\); \( Z \) is the carryover factor which can be fixed, free, good, or bad; and \( W \) depicts the weights. See the diagram below for further details which is denoted by Figure 1.

The nonoriented Tone and Tsutui32 model is formulated as

\[
E_{o} = \min \left[ \frac{1}{T} \sum_{t=1}^{T} W_{t} \left( 1 - \frac{1}{m+nbad} \left( \sum_{i=1}^{m} w_{t}^{i} x_{it} + \sum_{nbad}^{i=1} x_{it}^{nbad} \right) \right) \right] \\
E_{o} = \min \left[ \frac{1}{T} \sum_{t=1}^{T} W_{t} \left( 1 + \frac{1}{n+good} \left( \sum_{i=1}^{n} w_{t}^{i} x_{it} + \sum_{good}^{i=1} x_{it}^{good} \right) \right) \right]
\]

\[
\sum_{j=1}^{n} z_{j1}^{t} \lambda_{j}^{t} = \sum_{j=1}^{n} z_{j1}^{t+1} \lambda_{j}^{t+1} \quad (\forall i; t = 1, \ldots, T-1) \tag{2}
\]

Equation (2) serves as the linking factor connecting the two consecutive periods dynamically

\[
x_{tot}^{t} = \sum_{j=1}^{n} x_{ijt} \lambda_{j}^{t} + s_{it}^{-} \quad (i = 1, \ldots, m; t = 1, \ldots, T)
\]

\[
x_{tot}^{fix} = \sum_{j=1}^{n} x_{ijt}^{fix} \lambda_{j}^{t} \quad (i = 1, \ldots, p; t = 1, \ldots, T)
\]

\[
y_{tot}^{t} = \sum_{j=1}^{n} y_{ijt} \lambda_{j}^{t} - s_{it}^{+} \quad (i = 1, \ldots, s; t = 1, \ldots, T)
\]

\[
y_{tot}^{fix} = \sum_{j=1}^{n} y_{ijt}^{fix} \lambda_{j}^{t} \quad (i = 1, \ldots, r; t = 1, \ldots, T)
\]

\[
z_{tot}^{good} = \sum_{j=1}^{n} z_{j1}^{t} \lambda_{j}^{t} - s_{it}^{good} \quad (i = 1, \ldots, ngood; t = 1, \ldots, T)
\]

\[
z_{tot}^{bad} = \sum_{j=1}^{n} z_{j1}^{t} \lambda_{j}^{t} + s_{it}^{bad} \quad (i = 1, \ldots, nbad; t = 1, \ldots, T)
\]

\[
z_{tot}^{free} = \sum_{j=1}^{n} z_{j1}^{t} \lambda_{j}^{t} + s_{it}^{free} \quad (i = 1, \ldots, nfree; t = 1, \ldots, T)
\]

\[
z_{tot}^{fix} = \sum_{j=1}^{n} z_{j1}^{t} \lambda_{j}^{t} \quad (i = 1, \ldots, nfix; t = 1, \ldots, T)
\]

\[
\sum_{j=1}^{n} \lambda_{j}^{t} = 1 \quad (t = 1, \ldots, T)
\]

\[
\lambda_{j}^{t} \geq 0, s_{it}^{-} \geq 0, s_{it}^{+} \geq 0, s_{it}^{good} \geq 0, s_{it}^{bad} \geq 0 \text{ and } s_{it}^{free} \geq 0 (\forall i, t)
\]

Here is the most efficient, feasible solution:

\[
E_{ot} = \frac{1}{1 + \frac{1}{m+nbad} \left( \sum_{i=1}^{m} w_{t}^{i} x_{it} + \sum_{nbad}^{i=1} x_{it}^{nbad} \right) \left( \sum_{i=1}^{nbad} z_{i1}^{t} \lambda_{i}^{t} \right)} \tag{4}
\]

\[
E_{ot} = \frac{1}{1 + \frac{1}{n+good} \left( \sum_{i=1}^{n} w_{t}^{i} x_{it} + \sum_{good}^{i=1} x_{it}^{good} \right) \left( \sum_{i=1}^{ngood} z_{i1}^{t} \lambda_{i}^{t} \right)} \tag{4}
\]

### 2.2 Projection analysis

On the contrary, DMU \( j \) is not efficient if \( s_{it}^{-} \neq 0, s_{it}^{+} \neq 0, s_{it}^{good} \neq 0 \), \( s_{it}^{bad} \neq 0 \) \( (\forall i, t) \), and \( \theta_{it} \leq 1 \) \( (\forall i) \). Considering these optimal solutions, the inputs, outputs, and carryover variables can further undergo projections or adjustments for each understudy DMU \( j \) as:

\[
\bar{x}_{it} = x_{it} - s_{it}^{-} \quad (i = 1, \ldots, p; t = 1, \ldots, T)
\]

\[
\bar{y}_{it} = y_{it} + s_{it}^{+} \quad (i = 1, \ldots, p; t = 1, \ldots, T)
\]

\[
\bar{m}_{it} = m_{it}^{good} + z_{i1}^{good} \quad (i = 1, \ldots, ngood; t = 1, \ldots, T)
\]

\[
\bar{m}_{it} = m_{it}^{bad} - z_{i1}^{bad} \quad (i = 1, \ldots, nbad; t = 1, \ldots, T)
\]

When the DMU \( k \) is projected, it will have an overall efficiency.

### 3 RESULTS

#### 3.1 Data used

The study covers 25 sampled African countries from 2007-2014. The data were obtained from the World Bank Indicators and the United Nations statistics division database in 2019. One challenge in data collection is that most of the African countries had a lot of missing data, and because of this situation, the sample covers only 25 countries out of a total of 54 countries in Africa. African economies with missing data in one or more of the investigated variable were excluded from the sample. Besides, data from 2015 upwards for energy consumption as well as other variables for these sampled countries in Africa were not found from the WDI and other online databases.

The selection of variables is important for any DEA model. In practice, a nation utilizes a lot of multiple inputs to adequately help in generating GDP. A lot of empirical research has been carried out worldwide to estimate energy efficiency.\(^{4,5,7,9}\) Following these prior studies and data availability, labor, capital stock, and energy use are described as the three inputs. The output variable is output GDP (gross domestic product), and CO₂ emission is used as the only undesirable output factor. Energy stock is carryover factor in this study. Note energy stock is computed based on the differentials in energy supply and its functional utilization for each nation.\(^{57}\)
Furthermore, considering the important role carryover factors play in efficiency evaluation, the study employs energy stock as good carryovers that relate to the profit orientation or carried forward energy stock to the next year. The central aim of this study is to advocate for all governments in Africa to seriously consider CO2 emissions reduction in the pursuit of economic prosperity. Thus, the performance of energy stock in year one period affects the efficiency of the next term. Energy efficiency studies that adopt a similar approach in assigning dynamic carry-over factors included.4,57,59 We present the definition of these variables in Table 1.

The study data were collected from two different sources WDI and UN data as stated above. This study covers a very long period for a thorough and profound better understanding of the analysis and discussions. The average descriptive statistics of the understudy variables are shown in Figure 2.

In Figure 2, the average values of labor kept rising for the entire sampled period. Again, the mean CO2 emission values continued increasing for the entire sampled period except for a slight decrease in the year 2010. Noticeable again is the average GDP values that continued increasing from the whole sampled period. Furthermore, from 2009 to 2014, both the energy and capital stocks mean values have witnessed incremental rates, while energy consumption average estimates experienced variation with time across the study period.

3.2 | Dynamic energy efficiency estimates in Africa

First, this study computed the overall energy efficiency (OE) and the term efficiency (TE) for the 25 selected African countries according to Equation (4). Table 2 shows the overall energy efficiency estimates of the 25 sampled African countries from 2007 to 2014.

From Table 2, the mean overall efficiency estimate is 0.519 for the entire sample period, implying 48.1% inefficiency levels or loss in productivity. As DEA calculates efficiency scores relative to the best or most efficient frontiers, we observe that countries in Africa are not the same, implying they are highly heterogeneous relative to their efficiencies. In terms of years, the overall average efficiency (0.519) has over performed the average overall efficiencies in the following years: 2009, 2012, 2013, and 2014. Only 5 African economies (Egypt, Eritrea, Gabon, Nigeria, and South Africa) are computed to be efficient for the entire sample period. Also, Cote d’Ivoire has the best efficiency from 2007 to 2011 but its performance dropped significantly in the later years. Congo, Dem. Rep., and Zimbabwe had efficient scores from 2007 to 2008, but they experienced fluctuation efficiency scores during the other years. The rest of the countries were estimated to be inefficient.

As Zhao et al. reports geopolitics or political unrest situations can greatly affect efficiency. Besides, the effects of

| Type   | Variable      | Definition                                                                 | Source  |
|--------|---------------|---------------------------------------------------------------------------|---------|
| Inputs | Capital stock | Capital stock (Millions of US dollars)                                    | WDI     |
|        | Labor         | Total Labor force (Millions of workers)                                   | WDI     |
|        | Energy use    | Energy consumption (kg of oil equivalent per capita)                      | WDI     |
| Output | GDP           | Gross domestic product (Millions of US dollars)                           | WDI     |
|        | CO₂ emission  | Carbon dioxide emission (Kilotons)                                        | WDI     |
| Carryover | Energy stock | Measured by the difference between energy supply and energy own use in each country | UNDS    |

Note: WDI and UNDS represent the World Development Indicators and United Nations Statistics Division respectively.
other external environmental factors such as energy resource structure, degree of industrialization, trade, and CO₂ emissions can have an instrumental impact on energy efficiency.

The above analysis demonstrates that carryover factor activities, as well as undesirable output factors (CO₂ emissions), have serious implications on energy efficiency in Africa. Therefore, the reduction of CO₂ emissions and the effective use of other input factors will drastically increase the output of these selected countries in Africa.

In detail, Figure 3 shows the patterns and trends of the mean energy efficiency measures of the selected African countries over time. It can be observed that Mozambique (0.21) had a lower overall mean efficiency score. The average efficiency estimates of Egypt, Eritrea, Gabon, Nigeria, South Africa appear as the highest. This is followed by Zimbabwe, Cote d’Ivoire, Algeria, and Kenya, with 0.84, 0.78, 0.67, and 0.67 efficiency scores, respectively.

The results of this study to a large extent attest to the findings of Guo et al., estimating the dynamic energy performance of selected OECD nations from 2000 to 2010. They found the overall average efficiency estimates to be 0.78 when only energy stock is used as a carryover factor. Again, Lu and Lu assessed the dynamic energy efficiency of 28 sampled European Union nations during the period 2009 to 2013. They deployed only GDP as the carryover factor and obtained an overall mean efficiency score of 0.743. Furthermore, Lu et al. investigated the dynamic energy efficiency among 48 selected high-income economies from 2010 to 2014 and obtained an overall mean efficiency score of 0.687.

3.3 Africa economies Projection difference Analysis of the inputs/outputs from 2007 to 2014

This study further analyzes the understudied inputs, outputs, and the crossover factors adjustment or projection ranges of African economies from 2007 to 2014. The purpose of such an analysis is to provide a benchmark for the inefficient economies to systematically achieve energy efficiency or be projected onto the contemporaneous frontier by Equation (5). When the computed projection value is positive, it means we should add input/output in that particular year. On the other hand, a negative value implies a reduction of the input/output. The results are displayed as follows.

In analyzing Table 3, one can notice clearly that most of the African countries had projection values to be negative on the input variables. (A) Capital stock: 8 African economies (Cote d’Ivoire, Congo, Dem. Rep, Egypt, Arab Rep., Eritrea, Gabon, Nigeria, South Africa, and Zimbabwe) required no adjustment in their capital stock since their calculated values were zero. The implication here is that rest of the African economies should adequately reduce their capital input to be efficient. Also, Benin, Algeria, Kenya, Mozambique, Niger, Senegal, and Tanzania have projection differences of capital to be below 50% in their estimated inefficiency values, which implies those countries needed to systematical reduce their capital to be efficient. The result further shows that the highest reduction adjustment of 86.18% for Sudan and the lowest of 11.85%...
for Togo. Finally, the capital input in African economies needs reduction by 33.28% on an annual average basis from 2007 to 2014. (B) Labor: The labor input for the selected African economies during the entire sample period should have been decreased by 26.69%. Further, only five African economies (Egypt, Arab Rep., Eritrea, Gabon, Nigeria, and South Africa) are efficient and require no adjustment in their labor inputs. However, Angola, Botswana, Algeria, Mauritius, and Tunisia had a higher adjustment in labor inputs relative to the overall mean. The managerial implication, those African economies, requires the highest reduction or improvement in labor to be efficient. We observe that inefficiency value of Niger (6.76%), Congo, Dem. Rep. (7.67%), Tanzania (10.60%), Togo (11.64%), and Benin (12.59%) which implies they require less than 20% reduction of labor to be on the contemporaneous frontier. (C) Energy consumption: Table 3 shows that from 2007 to 2014, energy consumption as input for African economies.

| Countries         | Overall efficiency (OE) | Term efficiency (TE) | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 |
|-------------------|-------------------------|----------------------|------|------|------|------|------|------|------|------|
| Angola            | 0.45                    |                      | 0.49 | 0.48 | 0.35 | 0.48 | 0.47 | 0.47 | 0.45 | 0.46 |
| Benin             | 0.32                    |                      | 0.44 | 0.31 | 0.24 | 0.34 | 0.34 | 0.34 | 0.27 | 0.25 |
| Botswana          | 0.26                    |                      | 0.38 | 0.25 | 0.18 | 0.24 | 0.21 | 0.21 | 0.28 | 0.32 |
| Cote d’Ivoire     | 0.78                    |                      | 1    | 1    | 1    | 1    | 1    | 0.59 | 0.34 | 0.32 |
| Cameroon          | 0.23                    |                      | 0.27 | 0.21 | 0.16 | 0.26 | 0.22 | 0.24 | 0.25 | 0.22 |
| Congo, Dem. Rep.  | 0.37                    |                      | 1    | 1    | 0.17 | 0.11 | 0.13 | 0.24 | 0.16 | 0.16 |
| Congo, Rep.       | 0.14                    |                      | 0.16 | 0.11 | 0.11 | 0.15 | 0.14 | 0.17 | 0.16 | 0.13 |
| Algeria           | 0.67                    |                      | 0.68 | 0.93 | 0.49 | 0.70 | 0.67 | 0.67 | 0.65 | 0.61 |
| Egypt, Arab Rep.  | 1                       |                      | 1    | 1    | 1    | 1    | 1    | 1    | 1    | 1    |
| Eritrea           | 1                       |                      | 1    | 1    | 1    | 1    | 1    | 1    | 1    | 1    |
| Gabon             | 1                       |                      | 1    | 1    | 1    | 1    | 1    | 1    | 1    | 1    |
| Ghana             | 0.30                    |                      | 0.29 | 0.35 | 0.22 | 0.31 | 0.34 | 0.29 | 0.30 | 0.27 |
| Kenya             | 0.67                    |                      | 0.43 | 0.62 | 1.00 | 1.00 | 1.00 | 0.63 | 0.34 | 0.36 |
| Morocco           | 0.63                    |                      | 0.61 | 0.71 | 0.52 | 0.67 | 0.63 | 0.67 | 0.62 | 0.63 |
| Mozambique        | 0.21                    |                      | 0.27 | 0.20 | 0.19 | 0.28 | 0.23 | 0.11 | 0.12 | 0.28 |
| Mauritius         | 0.33                    |                      | 0.45 | 0.29 | 0.28 | 0.30 | 0.32 | 0.32 | 0.33 | 0.33 |
| Niger             | 0.11                    |                      | 0.16 | 0.07 | 0.07 | 0.11 | 0.12 | 0.14 | 0.12 | 0.12 |
| Nigeria           | 1                       |                      | 1    | 1    | 1    | 1    | 1    | 1    | 1    | 1    |
| Sudan             | 0.36                    |                      | 0.39 | 0.38 | 0.34 | 0.39 | 0.38 | 0.35 | 0.35 | 0.34 |
| Senegal           | 0.32                    |                      | 0.36 | 0.21 | 0.19 | 0.35 | 0.39 | 0.34 | 0.36 | 0.39 |
| Togo              | 0.34                    |                      | 0.56 | 0.27 | 0.32 | 0.42 | 0.36 | 0.27 | 0.27 | 0.24 |
| Tunisia           | 0.45                    |                      | 0.52 | 0.45 | 0.33 | 0.46 | 0.46 | 0.46 | 0.48 | 0.45 |
| Tanzania          | 0.18                    |                      | 0.19 | 0.16 | 0.11 | 0.15 | 0.20 | 0.21 | 0.22 | 0.21 |
| South Africa      | 1                       |                      | 1    | 1    | 1    | 1    | 1    | 1    | 1    | 1    |
| Zimbabwe          | 0.84                    |                      | 1    | 1    | 0.53 | 0.63 | 0.56 | 1.00 | 1.00 | 1.00 |
| Mean              | 0.519                   |                      | 0.586| 0.560| 0.472| 0.534| 0.527| 0.509| 0.482| 0.483|
economies should have been greatly decreased by −19.37% on average. Eight African economies (namely: Congo, Dem. Rep, Egypt, Eritrea, Gabon, Morocco, Nigeria, South Africa, and Zimbabwe) had no energy use adjustment needs since their computed value was 0. Furthermore, it can be seen that the computed inefficiency value of Cameroon (61.38%), Senegal (48.30%), Ghana (47.50%), Tunisia (37.20), Niger (39.41%), and Tanzania (35.26%) are the highest. Clearly, this partly explained why these six countries recorded lower efficiency relative to the other African countries.

Further, we analyze the output factors projection difference as follows. (A) GDP: Gross domestic product (GDP) is an important determinant of energy efficiency evaluation. This is because the utilization of energy with the other inputs will greatly help generate GDP for every economy. Therefore, the adjustment ratios for GDP as a desirable output factor for the selected African economies are summarized below: The overall mean GDP of the sampled 25 African countries from 2007 to 2014 was 39.03%. The country requiring the most adjustment was Mozambique with 82.71%, Mauritius (81.15%), Botswana (76.56), Tanzania (79.54), and Niger (76.38%). The managerial implication these countries appear to have experienced growth in GDP or reduce their consumption of the input factors in the next period to be efficient. In total, 8 African countries (Angola, Egypt, Eritrea, Gabon, Nigeria, Sudan, South Africa, and Zimbabwe) did not require further adjustment in their GDP from 2007 to 2014. The rest of the African economies being evaluated require increment in their GDP, to ensure energy efficiency improvement, as reported in Table 3. (B) CO2 emissions: From Table 3, CO2 emissions in African economies needed a drastic reduction by 3.32% on average from 2007 to 2014. Only 5 African economies (Egypt, Eritrea, Gabon, Nigeria, and South Africa) did not require adjustment in CO2 emissions. The implication here is that these countries were able to find the balance between emission reduction and economic growth. Therefore, they can serve as the benchmark for the remaining African economies to emulate. The rest of the sampled countries need to reduce emission figures to be efficient.
3.3.1 Annual projection of energy stock as a carryover factor of African economies from 2007 to 2014

In this section, we show the results of the projection value for the crossover intermediate factors as evaluated by the dynamic model. Should the computed value be negative; we should reduce excess energy stock to enhance efficiency. If the estimated value is positive, it implies a shortage of energy stock and the target DMU should add more stock to ensure efficiency improvement. The central theme of the dynamic DEA model employed for this study is to measure each economy’s crossover inefficiency change over time. The basic DEA model cannot link the input/output factors dynamically. The addition of energy stock in this study is serving as the connecting factor between the input and output factors. The selection of the energy stock was based on the profit orientation or economic basis for African economies to be linked to the next year’s time period. Again, Guo et al.\(^57\) argued that energy stock is a significant determinant of energy efficiency and should be adopted as a carryover factor in dynamic DEA modeling. It can be employed to greatly help indicate the performance gap among the investigated DMUs.

From Table 4, we observe that the mean overall inefficiency ratio of 40.04% shows a reduction phenomenon. The mean inefficiency estimates for 2008 and 2011 show a lower mean level relative to the entire period mean. The study results demonstrate three emerging situations: (a) The overall crossover inefficiency mean estimate for 2013 appears as the highest comparing with the other years. Regrettably, 20 African economies had mean inefficiency estimates that are negative for the entire study period. Algeria recorded the highest average inefficiency estimate of 113.43%. Following Algeria is Morocco (110.39%), Congo, Dem. Rep, (96.85), Angola (90.87%), and Mozambique (75.08%). We do not find any of the African economies to have a positive inefficiency mean estimate, implying these economies should reduce energy stock to improve their relative efficiency. (b) Only five African economies (Egypt, Eritrea, Gabon, Nigeria, and South Africa) do not require adjustment in their energy stock

| Countries          | 2007  | 2008  | 2009  | 2010  | 2011  | 2012  | 2013  | 2014  | Mean  |
|--------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Angola             | −82.64| −76.01| −102.02| −97.01| −94.38| −85.30| −91.06| −98.53| −90.87|
| Benin              | −20.27| −26.07| −25.69| −24.77| −24.77| −24.41| −24.41| −28.23| −24.83|
| Botswana           | −12.17| −18.48| −16.64| −13.98| −14.76| −14.40| −13.29| −14.34| −14.76|
| Cote d’Ivoire     | 0     | 0     | 0     | 0     | 0     | −98.00| −98.00| 0     | −24.50|
| Cameroon           | −84.95| −80.84| −70.79| −66.81| −71.95| −70.30| −65.28| −70.76| −72.71|
| Congo, Dem. Rep.  | 0     | 0     | 0     | 0     | 0     | −137.41| −120.64| −120.64| −127.71|
| Congo, Rep.       | −31.37| −30.15| −27.81| −24.67| −19.06| −17.81| −17.81| −31.72| −25.05|
| Algeria            | −113.70| −112.99| −118.95| −114.92| −112.63| −103.27| −101.25| −129.77| −113.43|
| Egypt, Arab Rep.  | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| Eritrea            | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| Gabon              | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| Ghana              | −113  | −66.36| −44.54| −50.93| −50.93| −55.72| −52.03| −58.55| −61.49|
| Kenya              | −146  | 0     | 0     | 0     | 0     | −93.71| −97.24| −106.64| −55.41|
| Morocco            | −104.17| −107.83| −122.36| −111.86| −108.76| −101.15| −109.07| −117.91| −110.39|
| Mozambique         | −70.12| −76.00| −81.04| −80.25| −75.79| −78.71| −74.34| −64.43| −75.08|
| Mauritius          | −7.28 | −7.74 | −7.57 | −6.82 | −6.96 | −6.65 | −7.23 | −7.21 | −7.18 |
| Niger              | −7    | −7.99 | −9.94 | −5.32 | −5.45 | −4.26 | −4.26 | −5.77 | −6.20 |
| Nigeria            | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| Sudan              | −54.17| −53.29| −60.64| −56.11| −55.31| −52.08| −53.42| −62.92| −55.99|
| Senegal            | −8.78 | −10.03| −9.70 | −43.52| −43.52| −46.06| −50.25| −8.61 | −27.56|
| Togo               | −13.22| −14.90| −12.94| −13.48| −13.80| −14.34| −14.34| −13.92| −13.92|
| Tunisia            | −50.84| −45.29| −43.08| −35.87| −37.76| −35.89| −35.89| −42.14| −40.84|
| Tanzania           | −99   | −10.58| −11.25| −60.76| −60.76| −59.32| −56.36| −64.28| −52.79|
| South Africa       | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| Zimbabwe           | 0     | 0     | −146.972| −102.50| 0     | 0     | 0     | 0     | −31.18|
| Mean               | −40.72| −29.78| −41.97| −41.21| −36.69| −43.82| −43.99| −42.15| −40.04|
values since the projection difference of those countries is zero. This implies that those African economies were able to balance the energy stock level to propel balance development between economic growth and CO₂ emission reduction. (c) Based on the inefficiency estimate of each country: Algeria appears to have more energy stock than the rest of the African economies and its inefficiency estimates range from 101.25% to 129.77%. This is followed by Morocco with inefficiency averages ranging between 101.15% and 122.36%, and next are Congo, Dem. Rep., and Angola in that order. Therefore, it is essential to emphasize that all these countries should control CO₂ emission and reduce their energy stock to improve efficiency.

Finally, what determinants lead to inefficiency situation in the crossover intermediate factors? A possible reason one can see clearly from the result is that energy stock is misused by the selected African countries. Therefore, selected African economies should reduce their energy stock to improve relative efficiency or control CO₂ emission reduction in their quest for economic prosperity. Overall, we contend that African economies could achieve energy efficiency by enhancing GDP and reducing CO₂ emission.

4 CONCLUSION AND POLICY IMPLICATIONS

In this study, we have applied the dynamic SBM-DEA model for the effective and profound energy efficiency assessment in Africa. It is essential to consider the inclusion of both desirable and undesirable output factors in DEA modeling, to generate fair efficiency estimates. Different from previous energy efficiency studies in Africa, the DSBM model allows for the measurement of energy efficiency within the multiple period frameworks. In this current study, energy stock is employed as dynamic link constraints connecting the two consecutive years \( (t \text{ and } t + 1) \) while CO₂ emission is treated as an undesirable output factor. This greatly helps in revealing all the possible sources of inefficiency and to obtain a deeper discrimination among investigated countries. The results suggest that the 25 sampled countries in Africa are far from the efficient frontier. Further, the study computed the output, input, and carryover activities inefficiency indicators in the estimated model, to adequately help the inefficient countries to improve their relative efficiency. That means sectoral regulators should pay attention to all the factors of production and both adjustments on the input, output, and carryover factors are essential to improving energy efficiency in Africa.

The policy implications based on the empirical results are twofold. First, it can be concluded that only 5 out of the entire sampled African countries investigated have efficient energy use. This implies that those countries can effectively and efficiently control emission reduction relative to their energy consumption planning policy. Second, the rest of the 20 sampled African economies that were estimated to be inefficient should drastically reduce waste in their resource utilization. Again, these countries must strengthen the control of CO₂ emission reduction measures and management policies; put forward various industrial policies in the form of emission cap laws; formulate or charge pollution taxes on mining industries; advocate energy-saving initiatives among households; invest in human capital development and energy-saving equipment; energy efficiency measures must be encouraged to minimize emission; and adopt clean energy sources such as solar, wind to minimize pollution to ensure effective energy use and reduction of CO₂ emissions.

One limitation of this study is the unavailability of recent data for the selected African countries. Most of the data for these countries are only up to the year 2014. We recommend that future studies should seriously consider the utilization of current data for this kind of analysis when such data are available. Future research could also analyze the impact of CO₂ emission and energy stock on energy efficiency in Africa for more than two years. Again, the determination of the weights is an important issue in DEA analysis; therefore, the effect of the weights on efficiency can be exploited for measuring the efficiency of the sampled countries in Africa. Other methods such as the Malmquist productivity index (MPI) can be used to investigate energy efficiency dynamics over time in Africa.

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