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# EVALUATION OF SUSTAINABLE ENERGY GENERATION EFFICIENCY BASED ON DATA ENVELOPMENT ANALYSIS USING PORTFOLIO THEORY: A LITERATURE REVIEW

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**Abstract**
Sustainable energy generation has become the solution approach to environmental issues associated with energy generation due to the ever-increasing global energy consumption and demand for sustainable development goals. The generation of secure and inexpensive clean energy is dependent upon the critical assessment of the associated risks and costs of diverse energy generation sources. To spread the associated risks with energy technologies, a portfolio optimization model is popularly used. Recently, policies on energy started including the environmental and social impacts of energy generation sources. As a result, sustainability has become paramount in energy mix design decisions. A sustainability goal in energy mix design aims to improve resource use and reduce environmental harm. Incorporating sustainability requires adding environmental and social cost indicators to total generation costs in portfolio optimization models. However, conventional methods often prioritize economic factors over environmental and social aspects. This review examines aggregation models and their impact on energy source preferences and optimized portfolios. It recommends multiplicative, pairwise interaction, and multi-linear aggregation models as more effective than additive models in integrating all sustainability dimensions for better energy mix decisions. Effective aggregation models helped include more renewable and clean energy sources in optimized energy portfolios. This study reviewed recent literature (2022–2025) on sustainable energy generation efficiency using data envelopment analysis (DEA). Among methods reviewed, the portfolio approach was found most effective due to its ability to diversify cost and risk across sustainability dimensions, aiding in technology assessment and optimal energy mix development.

## 1. Introduction

The rising global energy demand has led to significant environmental risks, particularly from greenhouse gas (GHG) emissions, highlighting the urgent need for balanced energy mix strategies. Energy mix involves various primary energy sources that generate electricity either directly or as a by-product. Designing innovative energy generation systems is a key priority for many countries. Awareness of the limitations of non-renewable sources, alongside social and environmental impacts of both renewable and non-renewable energy, has driven demand for clean, secure, reliable, and affordable energy solutions (Wu & Sansavini, 2021). Consequently, research increasingly focuses on sustainable energy generation mixes to mitigate carbon emissions through low-carbon, efficient technologies (Haugen et al., 2024), aligning with the UN Sustainable Development Goals (SDGs), particularly Goal 7 which advocates for affordable, reliable, sustainable, and modern energy for all (United Nations, 2015). Various methods have been applied to develop diversified energy portfolios addressing demand while minimizing environmental and social risks. Ioannou et al. (2017) reviewed risk-based sustainable energy design methods, highlighting mean-variance portfolio models, optimization techniques, and multi-criteria decision analysis (MCDA) as leading approaches. Early portfolio diversification concepts applied to energy design by Bar-Lev and Katz (1976), and later Awerbuch and Berger (2003), utilized mean-variance frameworks to assess technology costs and risks. Although initial models lacked a sustainability focus, recent developments incorporate energy security and climate change mitigation in sustainable generation mix design.

Modeling the economic, social, and environmental aspects of energy generation is essential to addressing sustainability challenges (Brandenburg et al., 2014; Li et al., 2024). Energy mix modeling integrates environmental and social costs with economic generation costs and risks to optimize portfolios (Bhattacharya & Kojima, 2012; Marrero et al., 2015). Total generation cost includes industrial costs (construction, operation, maintenance, fuel), $CO_2$ emissions, and external social/environmental costs (Arnesano et al., 2012). Adding $CO_2$ emission costs to levelized energy costs helps analyze renewable and non-renewable complementarities to reduce risks, costs, and emissions (Marrero et al., 2015). However, this conventional additive approach inadequately captures sustainability dimensions' interactions, potentially skewing portfolio outcomes and $CO_2$ mitigation (Cabello et al., 2019; Lo-Iacono-Ferreira et al., 2022). Additive models allow compensation of poor performance in some sustainability factors by others and overemphasize economic costs due to their larger contribution (82%) compared to social/environmental costs (18%) (Arnesano et al., 2012). As a result, portfolios tend to favor economic dimensions over equally critical social and environmental aspects. Alternative aggregation methods such as multiplicative, pairwise interaction, and multi-linear models better align with sustainability objectives and encourage greater inclusion of renewable and clean energy in optimized portfolios. Efficiently prioritizing all cost dimensions can lead to improved emission mitigation and environmentally friendly energy mixes.

Growing global concerns demand sustainable, secure, and affordable energy, necessitating efficient optimization and modeling to inform sound energy policies. This literature review examines how different cost structures influence preferences among energy generation technologies within portfolio optimization models, highlighting limitations of conventional methods in designing sustainable energy mixes. Traditional approaches often add social and environmental costs as weights to overall generation costs, but tend to prioritize economic factors over environmental and social dimensions, resulting in less effective sustainability outcomes. Previous studies have mostly focused on energy efficiency rather than the energy mix and sustainability goals. This review contributes by exposing the shortcomings of additive aggregation methods in incorporating social and environmental costs into energy portfolios. It proposes integrating multi-attribute utility theory with Data Envelopment Analysis (DEA) to better capture combined sustainability impacts and overcome conventional limitations. Novel DEA-based models are introduced to explore how aggregation methods affect technology rankings, revealing flaws in existing approaches. This critical analysis advocates for a more balanced, comprehensive framework for sustainable energy mix optimization. Ultimately, the study offers recommendations for generating energy portfolios with enhanced emissions mitigation potential, informing both policymakers and researchers about improving sustainable energy generation strategies.

Steps to achieve the objectives of this review research follows in the order of the ensuing sections. Section 2 details existing literature review. Section 3 conveys the methodological approach where various optimization models were developed to investigate the correlation among the various sustainability dimensions. Section 4 specifies the empirical analyses where the implications of different cost structures on the ranking of each of the technologies using the DEA approach are investigated. After, the implication of the cost structures on the optimal portfolio selected using the mean-variance framework would be next to follow. Concluding observations and recommendations is in the final section, Section 5.

## 1.1. Review of Existing Literature

The mean-variance framework for optimizing investment portfolios, introduced by Markowitz (1952), has been widely applied in energy design decisions. Early scholars like Bar-Lev and Katz (1976) and Awerbuch and Berger (2003) advocated using diversified portfolio theory to optimize energy mix portfolios. Later works by deLlano-Paz et al. (2017), Ahmadi et al. (2020), Malala and Adachi (2020), and Simoglou et al. (2022) continued applying this framework. The approach centers on estimating generation costs (returns) and associated risks for each technology, with total generation cost comprising economic (industrial) costs, external (societal) costs, and CO2 emissions costs (Awerbuch & Berger, 2003; Arnesano et al., 2012; Delarue et al., 2011; Kim et al., 2021). Economic costs include fuelling, construction, and operations and management (O\&M), while external costs capture environmental and societal impacts. However, some studies excluded external societal and environmental costs in optimization (Allan et al., 2011; Delarue et al., 2011; Mukherjee, 2010), focusing only on private costs like investment, O\&M, and fuel costs. Such portfolios prioritize secure, inexpensive energy but tend to favor non-renewable sources, ignoring the critical sustainability aspect of $CO_2$ emission mitigation and clean energy requirements essential for sustainable energy policies.

Some studies incorporate environmental and external impact costs into estimating expected generation costs, recognizing the importance of $CO_2$ emissions mitigation and energy efficiency targets in shaping power generation configurations (Novacheck & Johnson, 2017; Stempien & Chan, 2017; Westner & Madlener, 2010, 2011). These works address the conflict between energy security and sustainability goals (Stempien & Chan, 2017). Commonly, sustainability factors are integrated by adding environmental and social cost weights to generation costs, as seen in China's energy mix optimization combining investment, fuel, O\&M, and $CO_2$ emission costs (Zhu & Fan, 2010) or by summing economic, social, and environmental costs (Arnesano et al., 2012). This aligns with Awerbuch and Berger's (2003) approach that factors $CO_2$ market prices into total costs. However, because environmental and social costs typically represent a small fraction of total generation costs in additive aggregation models, their true impact may be overshadowed or compensated by economic factors, weakening sustainability outcomes. Some researchers have explored portfolios using exclusively renewable sources (Prol et al., 2024), yet such mixes often fail to meet global policy demands that require a balanced inclusion of both renewable and non-renewable sources. This review highlights the inefficiencies of traditional additive aggregation methods in fully capturing social and environmental costs, advocating for improved modeling approaches for sustainable energy portfolios.

Therefore, an innovative approach that integrates the multi-cost factors and the DEA energy efficiency analyses is presented in this paper which gives a better illumination on the combined effects of the cost parameters on the optimal energy mix portfolio and also remedies the ineptitude of the additive aggregation method, the conventional approach. This innovative DEA efficiency models are employed to examine the effects of the different aggregation methods on energy generation sources ranking. The shortcomings of the traditional approaches for sustainable energy generation mix are critically examined. This is pertinent so that decision and policy makers will be acquainted with the shortcomings of the traditional methods, and the need for a more balanced and robust approach. In conclusion, recommendations are given for the designing of a more sustainable energy generation mix with high emission mitigation capacity. Meanwhile, what the generation cost (returns), and the risk are made up of are mainly the reason for the variations in literatures reviewed as the cost implications have direct influence on the nature of the resultant optimal energy mix portfolio generated.

## 2. Method

### 2.1. Diversification of Portfolio

The estimation of the expected value (returns) and the risks associated to a portfolio of energy technologies are used in the portfolio optimization as required by the Markowitz's mean-variance framework (Markowitz 1952). The generation cost or the output aspects (Roques et al., 2010) is used to determine the portfolio expected return (Mari, 2014; Park et al., 2016). However, the inverse of the expected generation cost (returns) is commonly used in the maximization modeling in energy mix design (Delarue et al, 2011). The expected return of the portfolio or expected annual value of a portfolio is generally represented as Roques et al (2010).

$$\mathcal{E}(Rp) = \sum_{j=1}^{n} \omega j \mathcal{E}(Rj) \qquad (1)$$

The expected return of a portfolio/annual value of the portfolio, $\mathcal{E}\,(R_p)$, is constituted by the weighted sum of the returns of n number of technologies in a portfolio under study. The standard deviation of the technologies in the portfolio is used to evaluate the risk of the portfolio, given by;

$$\sigma p = \sqrt{(}\sum_{j=1}^{n} \omega 2j \ \sigma 2j + \sum_{j=1}^{n} \sum_{k=1}^{n} \omega j \ \omega k \ \sigma j \ \sigma k \ \rho jk \,) \qquad (2)$$

$$j \neq k$$

Where σj and σk denotes the standard deviation (risks) of technology j and technology k in the portfolio, and ρjk is the correlation between technologies j and k. The optimal portfolio with the maximum return would be determined through the maximization of the portfolio expected return subject to the constraint of the portfolio risk in the optimization modeling. Similarly, the minimization of the portfolio risk subject to the portfolio expected return as the constraint would be used to evaluate the portfolio's minimum-variance (risk). In the two evaluations, the condition exists for the weights to sum up to one, such that: $\sum_{j=1}^{n} \omega j = 1$. Additionally, there could be other capacity constraints as well as other upper and lower limit requirements to be evaluated regarding the optimal weights. This would be contingent on a country's' and international policy requirements on portfolio of energy mix (Lim et al., 2014; Liu et al., 2011).

## 2.2. Expected Return and Risk Decomposition

This review study aims to analyze the internal configuration of an energy technology's return, determined as the inverse of its total generation costs, including investment, operations and management (O\&M), fuel, $CO_2$ emissions, and external societal costs (Dyer Maut, 2016). These costs are broadly categorized into economic (industrial), $CO_2$ emissions (tariffs), and external societal costs resulting from health risks (Arnesano et al., 2012; Allan et al., 2011). Minimizing these combined costs per energy unit is essential for producing secure, reliable, affordable, and clean energy. Thus, generation cost and risk form the basis for preferring energy technologies to achieve a sustainable energy mix (Arnesano et al., 2012; Delarue et al., 2011). Assuming we disintegrate the generation cost into its individual sustainability cost variables, that is, the social, economic and environmental costs, the return expected and the variance (risk) of a certain technology *j* would be denoted as:

$$\mathcal{E}\,(Rj) = \sum_{r=1}^{s} \mathcal{E}(rr) \tag{3}$$

$$var(r_1 + \ldots + r_S) = \sum_{r=1}^{s} var(r_r) \tag{4}$$

Where $r_r = 1/\,Cr$.

The sustainability variables are independent with zero covariance, making additive aggregation flawed as disadvantages in some variables offset advantages in others. Viewing the problem via utility maximization and applying Von Neumann and Morgenstern's axioms allows modeling multi-attribute utility as a multi-linear function for sustainable energy mix preferences (Von Neumann and Morgenstern, 1947; Keeney and Raiffa, 1993; Stewart, 2005):

$$u(Y) = \sum_{r=1}^{s} k_r u_r(y_r) + \sum_{r=1}^{s} \cdot \sum_{t>r} k_{rt} u_r(y_r)\, u_t(y_t) + \ldots + k_{1,2,\ldots,s} u_1(y_1) u_2(y_2) \ldots u_s(y_s) \tag{5}$$

Where *k's* are scaling constants that maintain consistency. The sustainability dimension or attribute, $y_r$, is utility independent of its sister attributes, if the preference for lotteries with diverse levels of the attribute, $y_r$, is independent on certain fixed levels of the sister attributes (Stewart, 2005). Under conditions where all attribute subsets are mutually utility independent, large $CO_2$ emission reductions are preferred at comparable economic and social returns (Keeney & Raiffa, 1993; Stewart, 2005). The multi-linear utility function integrates both additive and multiplicative aggregations, with additive models applied if preferences depend only on marginal probability distributions, ignoring attribute interactions (Keeney & Raiffa, 1993). Sustainability, as defined by Elkington (1998), lies at the intersection of economic, environmental, and social objectives, requiring integrated consideration rather than trade-offs. Additive aggregation allows weaknesses in one sustainability dimension to be offset by strengths in another, conflicting with sustainability norms (Hacatoglu et al., 2015; Rowley et al., 2012; Elkington, 1998; Pomerol & Barba-Romero, 2000). For instance, in Japan, economic costs dominate (about 75%) total generation costs, while $CO_2$ costs contribute minimally, diminishing the latter's influence in optimization (Bhattacharya & Kojima, 2012; Awerbuch & Yang, 2007). Summing sustainability costs risks undervaluing environmental and social factors. Considering expected return as a product of sustainability dimensions captures interactions better, allowing preferences to vary with different attribute levels (Keeney & Raiffa, 1993). Since economic, social, and environmental costs are independent, their covariance is zero, influencing risk evaluation in sustainability assessments.

$$\mathcal{E}(\text{Ɽj}) = \prod_{r}^{s} = 1 \ \mathcal{E}(rr) \tag{6}$$

$$var(r_1 \ \ldots\ldots \ r_S) = \prod_{r=1}^{s} \left( var(r_r) + (\mathcal{E}\,[r_r])^2 \right) - \prod_{r=1}^{s} (\mathcal{E}\,[r_r])^2 \tag{7}$$

In the multi-linear utility function, equation (5), there are various levels of interactions among the sustainability variables as all three sustainability variables are required for the description of the sustainability concept, hence, the interaction among the three sustainability dimensions in deciding the energy technology expected return is what this review study is centered on. However, in a situation where a technology unit has a zero costs/returns value on some sustainability dimension, the use of the pairwise interaction (aggregation) model would be useful and is recommended. Optimization models to study the various interactions among sustainability dimensions will be presented in the succeeding section. In the later sections, the empirical testing of these models will be presented to show how the interactions among the sustainability variables impact the preference among technologies.

## 2.3. Modeling the Correlations between Sustainability Dimensions using DEA.

In the assessment of efficiency, DEA a dominant, quantitative modeling technique and a non-parametric assessment method using input/output variables is often used (Ramanathan, 2006; Zhou et al., 2008; Gan et al., 2019., An et al, 2020). The gap between the decision making unit (DMU) under assessment and the DEA frontier measures the efficiency value. DEA technique is a common and dependable method in the efficiency of energy measurement (Zhang, 2003; Zhang & Choi, 2013; Emrouznejad et al., 2018).

The use of Data Envelopment Analysis (DEA) in energy efficiency assessment generally falls into two groups based on input/output data structure. One group uses all inputs—capital, energy, labor—and a single desirable output, usually GDP, representing electricity generation and economic income. Selecting appropriate input/output variables is crucial for DEA modeling. Given the dominance of fossil-based energy and its environmental risks, scholars increasingly incorporate ecological factors in energy efficiency evaluation (Zhang et al., 2018; Hu & Wang, 2006; Honma & Hu, 2008; Mukherjee, 2008). Studies now consider both desirable outputs (GDP) and undesirable outputs such as $CO_2$, $SO_2$, waste gases, and pollutants from fossil fuels (Tao et al., 2020; Dyckhoff & Allen, 2001; Zhou & Ang, 2008; Zhang et al., 2015; Wu et al., 2017). For example, $CO_2$ and GDP have been used to assess energy efficiency in CDM countries and Chinese provinces (Zhang et al., 2018; Li & Lin, 2015; Zhang & Choi, 2013; Wang et al., 2012), as well as EU industries (Makridou et al., 2016; Feng & Wang, 2017). Some scholars expand assessment to multi-step generation, analyzing technologies independently or converting inputs to a standard coal equivalent (Wu et al., 2017; Zhu et al., 2014; Zhao et al., 2019; Hampf, 2014; Welch & Barnum, 2009; Mukherjee, 2008, 2010; Wang et al., 2018). Despite its strengths, DEA has been used more for efficiency assessment than energy mix balancing, though it holds potential for benchmarking energy portfolios (Edirisinghe & Zhang, 2007; Lim et al., 2014; Tarnaud & Leleu, 2018; Amin & Hajjami, 2021).

Data Envelopment Analysis (DEA), a powerful multi-criteria decision-making (MCDM) tool, is widely used to assess how different cost structures affect the scores and rankings of energy technologies. MCDM models have been methodologically enhanced to incorporate multiple variables and indicators in sustainability-focused studies (Doukas et al., 2010; Turkson et al., 2020). DEA offers advantages over other MCDM techniques by avoiding challenges with normalization, variable weighting, and aggregation when integrating economic, environmental, and social impacts in portfolio optimization (Cinelli et al., 2014; Wang et al., 2009). DEA enables the analysis of sustainability variables both individually and collectively, allowing examination of how variable structures influence composite scores. Improvements in DEA methods have further facilitated exploring different preference scenarios. Moreover, DEA has been extensively applied in portfolio optimization problems (Edirisinghe & Zhang, 2007; Basso & Funari, 2001; Liu et al., 2011; Zhou et al., 2018) and diverse sustainability evaluations (Thies et al., 2019; Zhou et al., 2018). These studies have laid the groundwork for using DEA in energy mix portfolio optimization, highlighting its effectiveness in balancing multiple sustainability dimensions within energy technology assessments.

### 2.3.1. The Correlation between Multi-linear Utility Function and DEA.

Multi-linear utility function model, equation (5), having a set of $Y = (y_1, y_2, \ldots, y_3)$ mutually utility independent variables is referred. The utility function, $U_r\,(y_r)$ of the *r*th variable is scaled by $k_r$, where $0 \leq k_r \leq 1$. The process for constructing the utility, $u(Y)$ function in the multi-attribute utility model in practical terms, will entail the evaluation of the partial utilities, $u_r\,(y_r)$ first, before employing qualitative judgments to determine the right scaling, and then utilizing other methodologies such as, Principal Component Analysis, Entropy Method or the Analytic Hierarchy Process (AHP) (Dyer Maut, 2016 and Yang et al, 2014). The correlation between the DEA methodology and the multi-variable utility model in evaluating the scaling factors was presented by Yang et al, 2014. As the attributes in model (5) are all 'more is better', DEA-Without Explicit Input (DEA-WEI), using the index data of the type, $y_{ir} = e_r / x_i$, where $e_r$ is the outputs and $x_i$ is the inputs, can be employed for the evaluation of the scaling factors (Yang et al, 2014) from the quadratic model below:

$$h = \text{Max } \sum_{r=1}^{s} \omega_r u_r(y_{ro}) + \sum_{r=1}^{s} \sum_{t>r} \omega_{rt} u_r(y_{ro}) u_t(y_{to}) + \ldots + \omega_{1,2,\ldots,s} u_1(y_{1o}) u_2(y_{2o}) \ldots u_s(y_{so}) \qquad (8)$$

$$\text{s.t. } \sum_{r=1}^{s} \omega_r u_r(y_{rj}) + \sum_{r=1}^{s} \sum_{t>r} \omega_{rt} u_r(y_{rj}) u_t(y_{tj}) + \ldots + \omega_{1,2,\ldots,s} u_1(y_{1j}) u_2(y_{2j}) \ldots u_s(y_{sj}) \leq 1$$

$$\omega_r \geq 0,\ j=1,\ldots,n,\ r=1,\ldots,s,\ t=1,\ldots,s$$

The scaling factors maximizing the multi-linear utility function of the alternative *0* under examination is determined by the objective function in model (8), subject to the constraints that for all the other alternatives denoted *j*, (*j* = 1, …., n), the same function assuming the chosen scaling factors would be less than or equal to unity (1). The dual type of the linear programming problem, model (8), could otherwise be preferred as an alternative solution, model (9) following:

$$\text{Max } \theta$$

$$\text{s.t } \sum_{j-1}^{n} z_j u_r(y_{rj}) \geq \theta u_r(y_{ro}), r=1,\ldots,s \qquad (9)$$

$$\sum_{j=1}^{n} z_j u_r(y_{rj}) u_t(y_{tj}) \geq \theta u_r(y_{ro}) u_t(y_{to}), r=1,\ldots,s, t=1,\ldots,s$$

$$\sum_{j=1}^{n} z_j u_1(y_{1j}) u_2(y_{2j}) \ldots u_s(y_{sj}) \geq \theta u_1(y_{1o}) u_2(y_{2o}) \ldots u_s(y_{so})$$

$$\sum_{j-1}^{n} z_j = 1$$

$$\theta \geq 1$$

$$z_j \geq 0, j=1,\ldots,n$$

From models (8) and (9), the optimal solution of (9) is the inverse of the optimal solution of (8). In the case of single input in an energy technology, with the return-risk problem, the constant returns to scale DEA model can be derived by direct conversion of the DEA-WEI ] (Liu et al., 2011), so that:

$$\text{Max } \theta$$

$$\text{s.t } \sum_{j=1}^{n} \lambda_j e_{rj} \geq \theta e_{ro} \qquad (10)$$

$$\sum_{j=1}^{n} \lambda_j x_j \leq x_o$$

$$\lambda_j \geq 0, j=1,\ldots,n, r=1,\ldots,s$$

Charnes, Cooper, and Rhodes, CCR (*i.e.* Constant Returns to Scale) model equivalent to the DEA-WEI model having only the additive term in the multi-linear function is shown in model (10) above. A CCR model indicating the interacting term is possible, but now under additional constraints. Developed in order to study the correlation among sustainability variables and how they impact the rankings of technologies are the DEA models based on CCR shown in the next sub-section.

### 2.3.2. DEA Modeling of Correlations between Sustainability Dimensions.

To study the interactions among sustainability variables, also called sustainability attributes or sustainability dimensions, and how they affect the ordinal ranking of energy technologies ($j = 1, \ldots, n$), DEA models based on CCR model is employed. The expected return, ($\mathcal{E}(r)$), assumed to be the output is maximized in the model, while the risk ($\sigma$), assumed to be the input is minimized in the model, as we can obtain from this section. The scores may be construed to be the risk-adjusted performance measure in each of the DEA models shown as expected returns are maximized at certain risks levels.

### Sustainability Dimensions Modeling using the Additive Method (1st Model)

DEA models with the expected return and risk indicated by equations (3) and (4) will be subjected to performance ranking as an initial step. The sum of the returns of the different sustainability variables that constitutes the generation cost of the technology are used as the technology returns by this model. The risk measure in model (11) means the square root of the variance given by model (4). Thus, technology return is conventionally evaluated by this method in portfolio optimization analysis.

$$\mathcal{E}_0{}^1 = \max_{z,\Phi} \Phi$$

$$\text{s.t} \quad \sum_{j=1}^{n} z_j \sigma_r \leq \sigma_o \tag{11}$$

$$\sum_{j=1}^{n} z_j \mathcal{E}(r_j) \geq \mathcal{E}(\mathrm{r_o}) \Phi$$

$$Z_j \geq 0, \; j = 1, 2, \ldots, n$$

The objective of the model (11), for technology *0,* is to obtain the maximum Pareto-efficient proportional increase in the expected return at a given risk level. Thus, there would be no chance for the increase of the return as no other technology has a better Pareto-efficient return-risk mixture. *Hence, 0 and 1 are the boundary conditions for the inverse of the score in model (11), while unity is the most efficient score* ($0 < \frac{1}{\Phi} \leq 1$). $\mathcal{E}(r_j)$ denotes the expected return score value for technology $j$ from the additive model, and $Z_j$, denotes a non-negative vector quantity depicting weights for technology, $j$. The derived model exhibits constant returns to scale also called CCR, as it has discriminatory characteristics. The portrayed model presents different sustainability dimensions interacting with each other but without the need for efficient performance on each of the sustainability variables, therefore, permitting compensation, thus, the rankings obtained from model (11) does not conform to the ideals of sustainability.

### Decomposition of the Sustainability Dimensions Model (2nd Model)

To solve the deficiency presented by the additive model (11), one method should be to describe the different sustainability attributes as independent outputs which permit the adoption of Pareto preference on each of the sustainability variables. Hence, the total return-risk of a technology are disintegrated into the three different sustainability variables presented as the separate/individual inputs/outputs under separate constraints, shown in model (12) following:

$$\mathcal{E}^{2}_{o} = \max \Phi \tag{12}$$

$z, \Phi$

s.t $\quad \sum_{j=1}^{n} z_j \sigma_{rj} \le \sigma_{ro} \qquad r = 1, \ldots, s$

$\sum_{j=1}^{n} z_j \mathcal{E}(r_{rj}) \ge \mathcal{E}(r_{ro})\Phi \qquad r = 1, \ldots, s$

$z_j \ge 0, \; j = 1, \ldots, n$

In model (12) above, there are three sustainability attributes having three individual expected return constraints and three individual risk constraints representing the returns and risks for the three independent sustainability attributes. In the portfolio analysis, the technology return and risk may be described as the weighted average in such a model. Since this model (12) permits individual investigation of preference on each sustainability attribute, it is preferred to the model presented in (11). Hence, the technology would be permitted by the model to select the sustainability attribute on which more emphasis would be placed in view of the weights, since weights are subject to local conditions and vary among technologies.

## Sustainability Dimensions Modeling using the Multiplicative Method (3rd Model)

To solve this sort of preference problem between the expected returns of various sustainability variables, since the concept of sustainability basically requires interaction among the sustainability variables, it would be suitable to interact the different sustainability variables under investigation. The mutual probability distribution only is explored in this model. Multi-attribute utility model with variable weights inclusive of interaction terms to express value judgments could be used for the extension of the DEA method as given by Yang et al, 2014. Thus, the three return estimates would be included as the interaction term to provide for the need for interactions among sustainability attributes as presented in (13). An evaluation of a new risk variable expressed as the product of the returns would be required by this new model. Included in model (13) is this new risk variable for each generation technology, denoted as, $\hat{o}j$. The expected return and risk are respectively evaluated using models (6) and (7).

$$\mathcal{E}^{3}_{o} = \max \Phi \tag{13}$$

$\boldsymbol{z, \Phi}$

s.t $\quad \sum_{j-1}^{n} z_j \, \hat{o}_j \le \hat{o}_o$

$\sum_{j-1}^{n} z_j \, \mathcal{E}(\prod^{s}_{r-1} r_{rj}) \ge \mathcal{E}(\prod^{s}_{r-1} r_{ro})\Phi$

$z_j \ge 0, \; j = 1, 2, \ldots, n$

From model (13), the social, economic and environmental dimensions of sustainability will be well represented and prioritized in the constitution of various technology units and the rankings generated from this model (13) is most conformable with the ideals of sustainability.

## Sustainability Dimensions Pairwise Correlations (4th Model)

From model (13), a possible problem arises from the influence of a zero score on any sustainability variable and the effect of such on the final ranking of technologies. Potential zero score on any sustainability dimension could entail that no evaluation of performance based on the other sustainability dimensions may be done. For example, in a renewable energy technology set-up, there may be no environmental cost when only direct emissions are put into consideration. A pairwise interaction as a compromise solution should be considered in such scenario as shown by model (14) below:

$$\mathcal{E}^{4}_{o} = \max \Phi \tag{14}$$

$z, \Phi$

s.t $\quad \sum_{j=1}^{n} z_j \, \hat{o}_{rtj} \leq \hat{o}_{rto}$, r=1,...,h -1,t=h+1,..., s

$\sum_{j=1}^{n} z_j \, \mathcal{E} \, (r_{rj} \cdot r_{rtj}) \geq \mathcal{E} \, (r_{ro} \cdot r_{to}) \Phi$, r=1,...,h -1,t=h+1,..., s

$z_j \geq 0, j = 1, 2 \ldots, n$

The standard deviations (risks) of the expected return for sustainability variables, *r* and *t* evaluated using the pairwise interaction, is denoted, $\hat{o}_{rtj}$ in model 14. Like in model (7), the variance is evaluated, but *r* as 2 in each instance. In model (14), there's provision for a potential zero score on a sustainability variable, while the interactions among sustainability variables as demanded by sustainability ideals are sustained by the model. By implication, model (14), investigates the other possible outcomes in the threesome bottom line structure, for instance, technologies which boosts environmental and social dimensions, but come at a high economic cost (socio-environmental efficient); economically-profitable technologies that sustains society, but with high environmental consequences (socio-economic efficient), and the ones with economic profitability, with no environmental liability, but with no satisfactory societal support (eco-efficiency) (Sykes and Trench, 2014). The average of the pairwise interaction measures the total expected return and risk of the technology under such consideration.

## Sustainability Dimensions Multi-linear Correlation Evaluation Model (5th Model)

Another compromise model that makes provision for the problem of zero value on sustainability dimensions and also takes into consideration the mutual impacts across interacting variables, model (15) is shown below. The marginal effects and the mutual impacts among the various sustainability dimensions are considered by this model, model (15) below:

$$\mathcal{E}^{5}_{o} = max \; \Phi \tag{15}$$

$z, \Phi$

s.t $\quad \sum_{j=1}^{n} z_j \left( \sum_{r=1}^{s} \sigma_{rj} + \hat{o}_j \right) \leq \left( \sum_{r=1}^{s} \sigma_{ro} + \hat{o}_o \right)$, r=1,…, s

$\sum_{j-1}^{n} z_j \, \mathcal{E} \left( \sum_{r-1}^{s} r_{rj} + \prod_{r-1}^{s} r_{rj} \right) \geq \mathcal{E} \left( \sum_{r-1}^{s} r_{ro} + \prod_{r=1}^{s} r_{ro} \right) \Phi$

$z_j \geq 0, j = 1, 2 \ldots, n$

## 3. Results and Discussion

In the application of real data in comparison with literature approach, Arnesano et al, 2012, data on the optimization of Italian electricity generation mix using portfolio theory is employed. They used societal (external costs), environmental ($CO_2$ costs), and economic (industrial costs) attributes to make up the generation cost in their evaluation. Per se, the three sustainability variables can be modeled in our evaluations in this section. In Arnesano et al, 2012, investigation, the correlation among the three variables was modeled as a sum. The inverse of the sum of the generation costs, consisting of the societal (external), direct and indirect $CO_2$ (environmental), and the economic (industrial) costs was maximized at a given risk associated with each generation technology unit.

### 3.1. Evaluation of Sustainability Dimensions using DEA

Arnesano et al. (2012) studied the Italian energy mix to identify alternatives minimizing financial costs and risks while considering environmental sustainability. Using a lifecycle assessment, environmental impacts included $CO_2$ costs and embodied emissions from renewables. External costs, reflecting societal impacts beyond plant expenses, represent the social sustainability attribute. The summarized data from the study for the ten (10) energy technologies available in the Italian energy mix consisting of both renewable and non-renewable energy sources are shown in Table 1 below.

**Table 1. Evaluation of Costs and Risks**

| Generation Technology | Environmental ($CO_2$) Cost | External (Societal) Cost | Economic (Industrial) Cost | Total Cost | Risk |
|---|---|---|---|---|---|
| Gas (100 - 160) | 0.423 | 2.500 | 9.893 | 12.816 | 11.02 |
| Gas (660) | 0.423 | 2.500 | 6.939 | 9.862 | 10.85 |
| Coal (100 – 160) | 0.816 | 5.850 | 5.487 | 12.154 | 15.48 |
| Coal (320) | 0.816 | 5.850 | 4.975 | 11.642 | 16.02 |
| Hydro (>10)* | 0.172 | 0.340 | 5.457 | 5.968 | 8.19 |
| Hydro (<10)* | 0.172 | 0.340 | 6.410 | 6.922 | 27.26 |
| Wind (>0.1 – 2)* | 0.041 | 0.150 | 13.293 | 13.484 | 3.75 |
| PV (0.5 – 1)* | 0.272 | 0.160 | 39.746 | 40.178 | 4.02 |
| Biomass (<15)* | 0.234 | 2.650 | 13.223 | 16.107 | 12.57 |
| Nuclear (1100) | 0.021 | 0.250 | 5.082 | 5.353 | 16.72 |

*= Renewable Energy Source Technology

Table 1 shows renewable technologies generally outperform non-renewables in environmental and social sustainability but face higher economic costs, as with PV solar (39.746 economic cost, 98.9% of total). Non-renewables have economic advantages, while nuclear shows lower costs despite higher risks. Portfolio optimization must balance these trade-offs (Arnesano et al., 2012). Likewise, the fossil-centered technologies, Gas (100 -160) and Gas (660), has economic (industrial) cost advantages and are among the high performers in the mix, but they're disadvantaged as one of the most risky technologies as regards to their environmental and social impacts. See Table 2 below.

**Table 2. Modeling of Sustainability Dimensions Using Additive Aggregation (1st Model)**

| Generation Technology | Return | Risk | Score | Rank |
|---|---|---|---|---|
| Gas (100 -160) | 0.08 | 11.02 | 0.3459 | 5 |
| Gas (660) | 0.10 | 10.85 | 0.4567 | 4 |
| Coal (100 -160) | 0.08 | 15.48 | 0.2598 | 8 |
| Coal (320) | 0.09 | 16.02 | 0.2620 | 7 |
| Hydro (>10) | 0.17 | 8.19 | 1.0000 | 1 |
| Hydro (<10) | 0.14 | 27.46 | 0.2571 | 9 |
| Wind (>0.1 – 2) | 0.07 | 3.75 | 0.9669 | 2 |
| PV (0.5 -1) | 0.02 | 4.02 | 0.3027 | 6 |
| Biomass (<15) | 0.06 | 12.57 | 0.2414 | 10 |
| Nuclear (1100) | 0.19 | 16.72 | 0.5459 | 3 |

The italicized values in Table 2 conform to the theoretical ideals as expected of energy technology ranking based on sustainability concepts, while the non-italicized values are not conformable with the ideals of sustainability theory as expected from energy technology ranking.

Next, the three sustainability attributes would be represented with independent outputs and inputs under different constraints by the disintegration of the total return owing to the 2nd Model [Eqn. 12] which follows the Pareto preference. Table 3 below illustrates. The estimated risk value for the social (external) sustainability dimension was not provided by the authors, Arnesano et al, 2012, because the historical data was not available, as such, no risk score (or constraints) for the social attribute of the sustainability is provided in this analysis also.

**Table 3. Sustainability Dimensions Decomposition (2nd Model [Eqn. 12])**

| Generation Technology | Environmental Return | Societal Return | Economic Return | Environmental Risk | Economic Risk | Score | Rank |
|---|---|---|---|---|---|---|---|
| Gas (100 – 160) | 2.36 | 0.40 | 0.10 | 0.86 | 10.99 | 0.4180 | 8 |
| Gas (660) | 2.36 | 0.40 | 0.14 | 1.12 | 10.80 | 0.5936 | 5 |
| Coal (100 – 160) | 1.23 | 0.17 | 0.18 | 1.75 | 15.38 | 0.5271 | 7 |
| Coal (320) | 1.23 | 0.17 | 0.20 | 1.83 | 15.92 | 0.5616 | 6 |
| Hydro (>10) | 5.81 | 2.94 | 0.18 | 0.75 | 8.15 | 1.0000 | 1 |
| Hydro (<10) | 5.81 | 2.94 | 0.16 | 0.64 | 27.45 | 0.2821 | 10 |
| Wind (>0.1 – 2) | 24.39 | 6.67 | 0.08 | 0.08 | 3.75 | 1.0000 | 1 |
| PV (0.5 – 1) | 3.68 | 6.25 | 0.03 | 0.18 | 4.02 | 0.8738 | 4 |
| Biomass (<15) | 4.27 | 0.38 | 0.08 | 0.38 | 12.56 | 0.2954 | 9 |
| Nuclear (1100) | 47.62 | 4.00 | 0.20 | 0.10 | 16.72 | 1.0000 | 1 |

The italicized values in Table 3 conform to the ideals as expected of energy technology ranking based on sustainability concepts, while the non-italicized values are not conformable with the ideals based on sustainability theory regarding expectations of energy technology ranking.

From Table 3, the variables being independently compared based on Pareto preference, shows that the preference assessment of the technologies is assumed to be relatively more consistent with sustainability principles than was shown in Table 2. Now, as each of the variables is compared across the technologies, there would be less discrimination than in the previous model when generating the overall score. Furthermore, technologies select the dimension to lay more emphasis on based on their weighting. Thus, the reason, why Gas (660) is among the best performers, as it emphasizes more weight on higher economic performance. Likewise, Coal (320) emphasizes more weight on high economic returns (low industrial costs); though it performs relatively poorly on the environmental and societal attributes. However, as emphasis could be placed on the advantage of one variable over another in this model, this model is not consistent with the basic sustainability concepts.

In the following section, we examine how the interaction between the expected returns of the various sustainability variables would impact the scores and the rankings of the technologies. As the case may be, these interactions conform more with the ideals of sustainability than offered by the additive aggregation method. However, as we can see from Table 3, the relatively high scores on the economic variable risks will lead to the transformation of the economic return variable which would now be transformed and substituted with the square root of the returns for each technology. Then, the risks are evaluated based on eqn. (7).

Table 4 elucidated a more conformable sustainability model as expected of the ranking of energy technologies, having the renewable sources and the nuclear technology among the best performers, and the non-renewable (fossil-centered) sources among the low performers. Wind, hydro, PV (solar), and nuclear technologies are among the high performers. To boost the better integration of all the three sustainability variables in the portfolio mix this interaction among the sustainability variables is needed and necessary. Nevertheless, it is necessary to inform that a zero value on any sustainability attribute will automatically result to no performance score for the concerned technology. A technology could be adjudged to have no associated environmental cost based on no direct emissions but not on the entire lifecycle emissions which would explain for the embodied emissions.

**Table 4. Sustainability Dimensions Modeling using the Multiplicative Method (3rd Model)**

| Generation Technology | Return | Risk | Score | Rank |
|---|---|---|---|---|
| Gas (100 – 160) | 0.30 | 0.1091 | 0.0060 | 7 |
| Gas (660) | 0.36 | 0.1694 | 0.0046 | 8 |
| Coal (100 – 160) | 0.09 | 0.1275 | 0.0015 | 9 |
| Coal (320) | 0.09 | 0.1398 | 0.0015 | 10 |
| Hydro (>10) | 7.32 | 0.9429 | 0.0170 | 6 |
| Hydro (<10) | 6.75 |  | 0.0197 | 5 |
| Wind (>0.1 – 2) | 44.60 | 0.1474 | 0.6609 | 2 |
| PV (0.5 – 1) | 3.64 | 0.1754 | 0.0454 | 3 |
| Biomass (<15) | 0.44 | 0.0391 | 0.0248 | 4 |
| Nuclear (1100) | 84.49 | 0.1845 | 1.0000 | 1 |

In the Multiplicative Aggregation Model, Table 4 above, we see a composite return, risk, score and rank values for all attributes. The renewable technologies outperforms the non-renewable technologies from the table owing to a fair dividend from all the sustainability dimensions (social, environmental and economic), with better weights on the social and environmental attributes, a property that most of the non-renewable technologies are lacking by which they portend very low/poor societal and environmental impact. These features of the renewable technologies have tremendously affected the total score and ranking of technologies.

To make provision for a special case of zero score on an attribute and the consequential effect on the final score, the application of a compromise solution is advocated and would be more appropriate. As provision is made for the possibility of zero score on a dimension, the result of the ranking would remain akin to what is obtainable in Table 4 above. Table 5 shows a scenario that integrates certain level of interactions among the sustainability variables and the consequential impact on the rankings based on the two compromise solutions: pairwise and multi –linear solutions. The renewable technologies show better performance than the non-renewables in the both compromise solutions, a condition that is consistent with the expectations of the ideals of sustainability and energy technology ranking.

**Table 5. The Compromise Solutions (4th and 5th Models)**

| | Pairwise interaction | | Multi-linear interaction | |
|---|---|---|---|---|
| Generation Technology | Score | Rank | Score | Rank |
| Gas (100 – 160) | 0.0869 | 7 | 0.0139 | 8 |
| Gas (660) | 0.0798 | 8 | 0.0142 | 7 |
| Coal (100 – 160) | 0.0573 | 10 | 0.0051 | 9 |
| Coal (320) | 0.0576 | 9 | 0.0050 | 10 |
| Hydro (>10) | 0.1340 | 6 | 0.0866 | 4 |
| Hydro (<10) | 0.1436 | 5 | 0.0285 | 5 |
| Wind (>0.1 – 2) | 1.0000 | 1 | 1.0000 | 1 |
| PV (0.5 – 1) | 0.4274 | 3 | 0.1632 | 3 |
| Biomass (<15) | 0.1710 | 4 | 0.0209 | 6 |
| Nuclear (1100) | 1.0000 | 1 | 0.4204 | 2 |

As the pairwise interactions accounts for the mutual effect among two variables at a time, the multi-linear model accounts for both the mutual effect among the three variables and also their marginal effects. Hence, the zero value on any one variable in a pairwise interaction will result to the expected return consisting of only the interaction effect between the remaining two variables. As a result, such a solution or technology will not override the counterpart where all the dimensions have no zero values. The multi-linear model is whereby the technology has an expected return consisting of both additive and multiplicative expressions. Consequently, a zero value on any dimension of sustainability will result to the technology having a lower expected return since only the additive component of the sustainability dimensions would be considered.

The Simar and Wilson (Simar and Wilson, 2000, and Simar and Wilson, 1998) bootstrapping method would be employed to evaluate the bias-adjusted scores for all the preceding risk-adjusted performance scores. This is as a result of the fact that outliers and statistical noise can have effect on DEA scores. Furthermore, the 95% confidence intervals (95% CI) would be shown for the bias-adjusted scores. The rankings of the technologies based from the bias-adjusted scores are in uniformity with the original evaluations obtained from the preceding tables. This is a confirmation that the results were not influenced by the existence of any outlier or statistical noise.

The comparison of all the different models discussed is presented in Table 6 below. The rankings among the technologies for each model would be presented in a heat-map as well as the correlation coefficient among the models. Obviously, it would be observed that the significant strong correlations among the 3rd Model and the two compromise models, 4th Model and the 5th Model emphasize the reliability of the interactions as an aggregation approach in representing all the dimensions in the ranking. The low/poor and insignificant correlation between the additive technique and the interaction models also authenticates and verifies the interaction models to represent the sustainability end-result based on all the sustainability variables considered than the additive modeling.

**Table 6. Correlations among the Five (5) Aggregation Models**

| Generation Technology | 1st Model | 2nd Model | 3rd Model | 4th Model | 5th Model |
|---|---|---|---|---|---|
| Gas (100 – 160) | 5 | 8 | 7 | 7 | 8 |
| Gas (660) | 4 | 5 | 8 | 8 | 7 |
| Coal (100 – 160) | 8 | 7 | 9 | 10 | 9 |
| Coal (320) | 7 | 6 | 10 | 9 | 10 |
| Hydro (>10) | 1 | 1 | 6 | 6 | 4 |
| Hydro (<10) | 9 | 10 | 5 | 5 | 5 |
| Wind (>0.1 – 2) | 2 | 1 | 2 | 1 | 1 |
| PV (0.5 – 1) | 6 | 4 | 3 | 3 | 3 |
| Biomass (<15) | 10 | 9 | 4 | 4 | 6 |
| Nuclear (1100) | 3 | 1 | 1 | 1 | 2 |

**Correlation Coefficients**

| Models | Coefficients | | | | |
|---|---|---|---|---|---|
| Model 1 | 1.00 | | | | |
| Model 2 | 0.88*** | 1.00 | | | |
| Model 3 | 0.28 | 0.41 | 1.00 | | |
| Model 4 | 0.29 | 0.41 | 0.99*** | 1.00 | |
| Model 5 | 0.52 | 0.61 | 0.92*** | 0.92*** | 1.00 |

P < 0.05 *, p < 0.01 **, p < 0.001***

Indicated are Spearman's correlation coefficients.

## 3.2. Optimal Generation Portfolio Development

From our previous discussions we have proved that the use of aggregation techniques for generating the cost per return structure used for the optimization of the energy mix portfolio can have impact on technology preference over another and on their rankings. Whether variations in the aggregate cost per return will impact the optimized portfolio of technologies developed using the Markowitz model should be our next focus. The maximum return and the minimum risk portfolios are the two portfolios that would be constructed for each of the cost structures investigated in the next study. The portfolio of technologies expected return is maximized subject to the risk and investment (capacity) constraints for the maximum return portfolio. An optimal portfolio of technologies that minimizes the overall portfolio risk is constructed for the minimum risk portfolio. The maximum return portfolio is the least diversified and used, while the minimum risk portfolio is most diversified and used portfolio. In the Italian case, the minimum and maximum capacity constraints of energy technologies considered indicating the lower and upper boundaries would be made available as supplementary information if need be.

Nuclear energy is excluded in the optimal portfolio of technologies presented in Table 7 and Figure 1 below. This is because the current Italian generation mix of technologies at the time of this investigation does not have nuclear generation option/input in the mix. $CO_2$ emissions were evaluated based on gas and coal options allocation using their respective emission factors of 55.82kg/GJ and 94.073kg/GJ, for an annual electricity demand of 314.57TWh consistent with Arnesano et al, 2012.

**Table 7. Optimal Portfolios Excluding Nuclear Option (Weighted)**

| | Source | Current Mix | Additive | | Multiplicative | | Pairwise | | Multi-linear | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Max Ret [a] | Min Risk [b] | Max Ret | Min Risk | Max Ret | Min Risk | Max Ret | Min Risk |
| | Portfolio Allocations | | | | | | | | | |
| 1 | Gas (100-160) | 0.18 | 0.02 | 0.14 | 0.02 | 0.14 | 0.02 | 0.20 | 0.02 | 0.14 |
| 2 | Gas (660) | 0.42 | 0.48 | 0.15 | 0.31 | 0.15 | 0.31 | 0.15 | 0.31 | 0.15 |
| 3 | Coal (100-160) | 0.04 | 0.04 | 0.07 | 0.00 | 0.07 | 0.00 | 0.07 | 0.00 | 0.07 |
| 4 | Coal (320) | 0.10 | 0.16 | 0.07 | 0.06 | 0.13 | 0.06 | 0.06 | 0.06 | 0.07 |
| 5 | Hydro (>10) | 0.15 | 0.18 | 0.18 | 0.18 | 0.11 | 0.18 | 0.11 | 0.18 | 0.18 |
| 6 | Hydro (<10) | 0.04 | 0.07 | 0.05 | 0.07 | 0.05 | 0.07 | 0.05 | 0.07 | 0.05 |
| 7 | Wind (>0.1-2) | 0.03 | 0.02 | 0.15 | 0.15 | 0.14 | 0.15 | 0.15 | 0.15 | 0.15 |
| 8 | PV (0.5-1) | 0.003 | 0.00 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| 9 | Biomass (<15) | 0.03 | 0.03 | 0.15 | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 | 0.16 |
| | Portfolio Characteristics | | | | | | | | | |
| | Portfolio Return | 0.10 | 0.11 | 0.10 | 8.79 | 7.79 | 10.94 | 10.34 | 8.89 | 8.73 |
| | Portfolio Risk | 6.42 | 6.64 | 4.56 | 0.19 | 0.12 | 0.19 | 0.14 | 5.21 | 4.67 |
| | % Renewables | 0.26 | 0.30 | 0.56 | 0.61 | 0.51 | 0.61 | 0.52 | 0.61 | 0.57 |
| | % Non-Renewables | 0.74 | 0.70 | 0.44 | 0.39 | 0.49 | 0.39 | 0.48 | 0.39 | 0.43 |
| | $CO_2$ Emissions [c] | 58.94 | 58.33 | 36.99 | 30.04 | 43.35 | 30.04 | 39.65 | 30.04 | 36.93 |

[a] Maximum return portfolio

[b] Minimum risk portfolio

[c] Measured in million tons

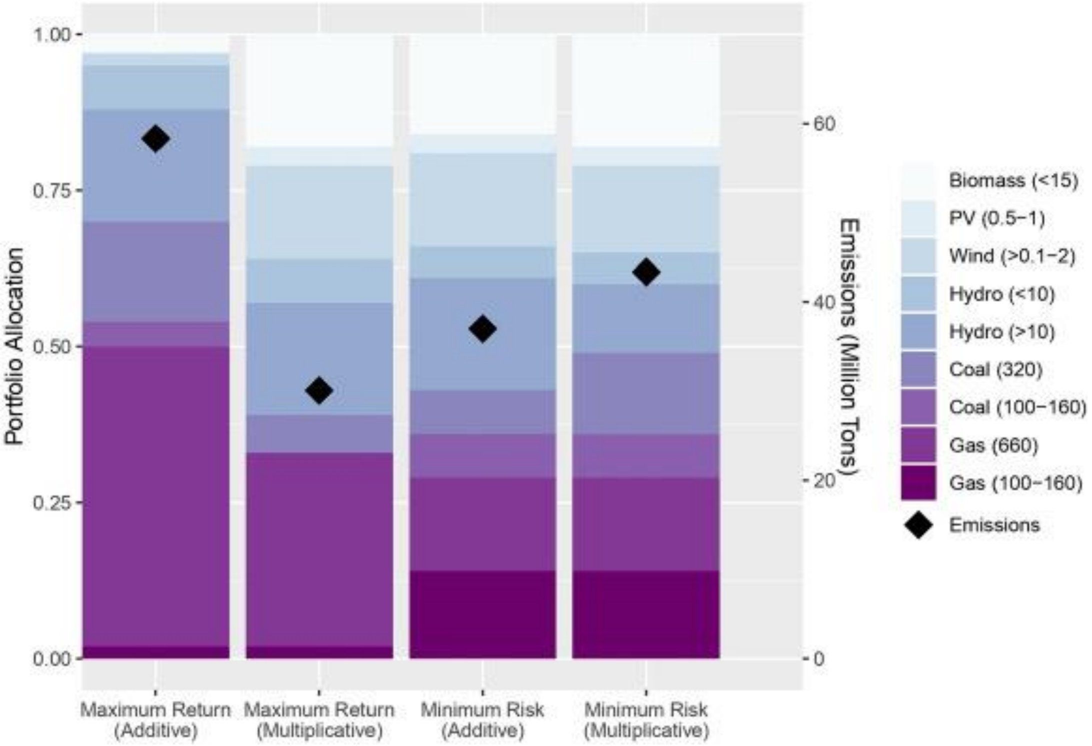

**Figure 1. Optimal Electricity Generation Mixes and CO$_2$ Emissions Excluding Nuclear Source**

Figure displays maximum return and minimum risk portfolios for both the additive and multiplicative aggregation of sustainability attributes.

Figure 1 reveals that the additive model (1st Model) allocates only 30% to renewables despite a 61% capacity limit, with gas dominating at 48%, excluding solar PV. Conversely, the multiplicative model (3rd Model) assigns 61% to renewables, resulting in significantly lower CO2 emissions and a cleaner energy mix. The additive model slightly outperforms the multiplicative model in minimum risk portfolios, partly due to missing social risk data, with both models showing similar renewable allocations (56% vs. 51%). Including nuclear energy in maximum return and minimum risk portfolios (Table 8, Figure 2) confirms these trends.

**Table 8. Optimal Portfolios Including Nuclear Option (Weighted)**

| | | Current Mix | Additive | | Multiplicative | | Pairwise | | Multi-linear | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Source | | Max Ret [a] | Min Risk [b] | Max Ret | Min Risk | Max Ret | Min Risk | Max Ret | Min Risk |
| | Portfolio Allocations | | | | | | | | | |
| 1 | Gas (100-160) | 0.18 | 0.02 | 0.10 | 0.02 | 0.10 | 0.02 | 0.04 | 0.02 | 0.10 |
| 2 | Gas (660) | 0.42 | 0.22 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 |
| 3 | Coal (100-160) | 0.04 | 0.00 | 0.05 | 0.00 | 0.07 | 0.00 | 0.01 | 0.00 | 0.05 |
| 4 | Coal (320) | 0.10 | 0.06 | 0.06 | 0.06 | 0.10 | 0.06 | 0.06 | 0.06 | 0.06 |
| 5 | Hydro (>10) | 0.15 | 0.18 | 0.18 | 0.14 | 0.11 | 0.11 | 0.11 | 0.14 | 0.18 |
| 6 | Hydro (<10) | 0.04 | 0.07 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 7 | Wind (>0.1-2) | 0.03 | 0.02 | 0.15 | 0.15 | 0.11 | 0.15 | 0.15 | 0.15 | 0.15 |
| 8 | PV (0.5-1) | 0.003 | 0.00 | 0.03 | 0.00 | 0.03 | 0.03 | 0.03 | 0.00 | 0.03 |
| 9 | Biomass (<15) | 0.03 | 0.03 | 0.13 | 0.03 | 0.18 | 0.03 | 0.18 | 0.03 | 0.13 |
| 10 | Nuclear (1100) | 0.00 | 0.40 | 0.10 | 0.40 | 0.10 | 0.40 | 0.22 | 0.40 | 0.10 |
| | Portfolio Characteristics | | | | | | | | | |
| | Portfolio Return | 0.10 | 0.15 | 0.11 | 41.93 | 14.92 | 38.52 | 25.70 | 42.07 | 17.16 |
| | Portfolio Risk | 6.42 | 7.72 | 4.29 | 0.17 | 0.12 | 0.13 | 0.13 | 7.44 | 4.40 |
| | % Renewables [d] | 0.26 | 0.70 | 0.64 | 0.77 | 0.58 | 0.77 | 0.74 | 0.77 | 0.64 |
| | % Non-Renewables | 0.74 | 0.30 | 0.36 | 0.23 | 0.42 | 0.23 | 0.26 | 0.23 | 0.36 |
| | CO$_2$ Emissions [c] | 58.94 | 23.77 | 30.43 | 18.89 | 36.98 | 18.89 | 21.65 | 18.89 | 30.36 |

[a] Maximum return portfolio
[b] Minimum risk portfolio
[c] Measured in million tons
[d] Percentage of clean energy i.e. renewable sources and nuclear energy

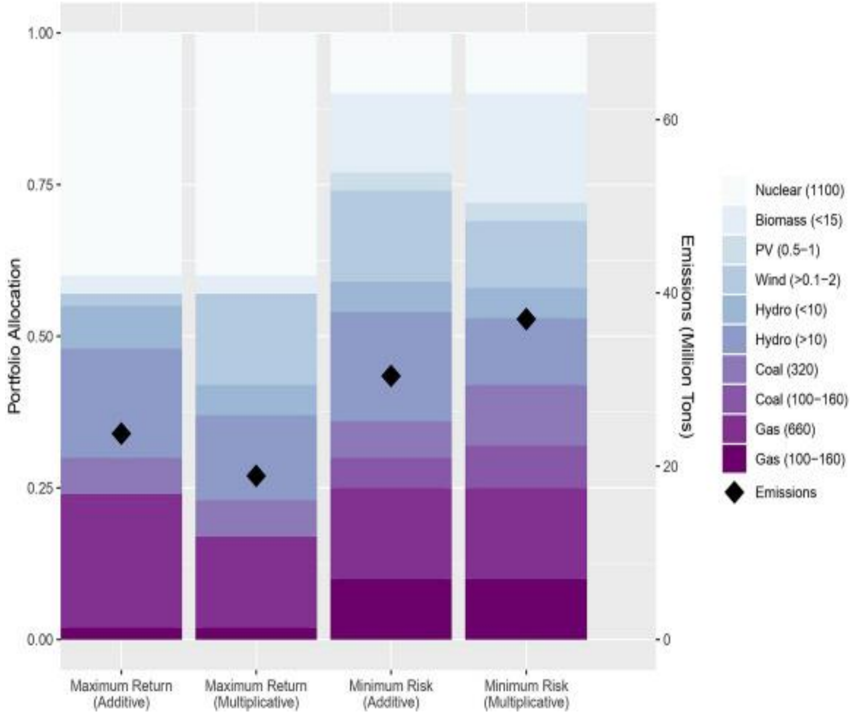

Figure 2. Optimal Electricity Generation Mixes and CO₂ Emissions Including Nuclear Source

Figure displays maximum return and minimum risk portfolios for both the additive and multiplicative aggregation of sustainability attributes.

In consideration of a situation that a sustainability dimension presents a zero value, the compromise solutions, pairwise and the multi-linear interactions/models would be employed. Figure 3 and figure 4 below presents the optimal portfolios of the two compromise models for without nuclear and nuclear options respectively. The figure 3 and figure 4 presents the optimal solutions in comparison to the current Italian generation mix and as well as the optimal solution generated by the multiplicative aggregation model. The comparison of the results shows that the maximum return of the three portfolios presents similar levels of $CO_2$ emissions, but regarding the minimum risk, the compromise solutions (pairwise and multi-linear models), presents better performance than even the multiplicative aggregation model.

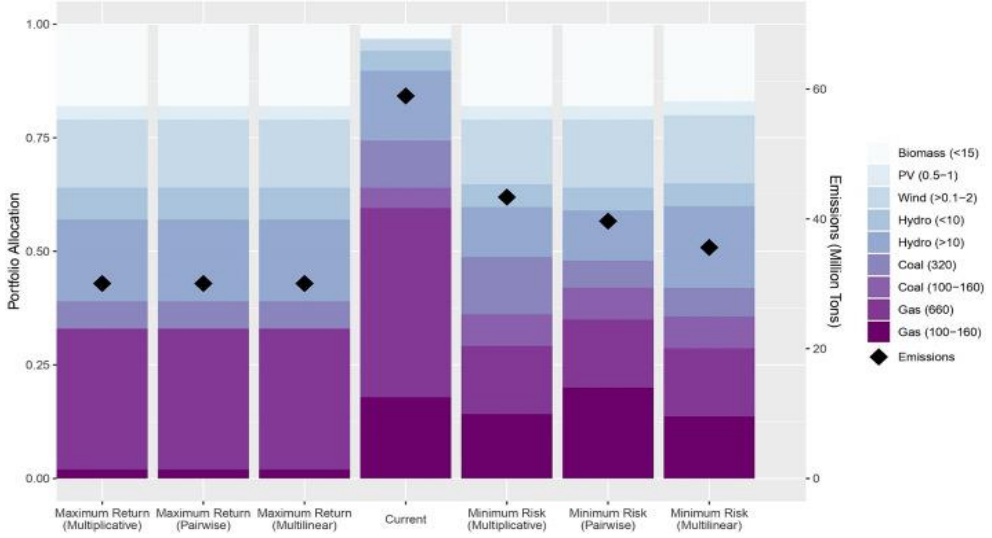

Figure 3. Compromise Solutions in Comparison to Other Solutions Excluding the Nuclear Source

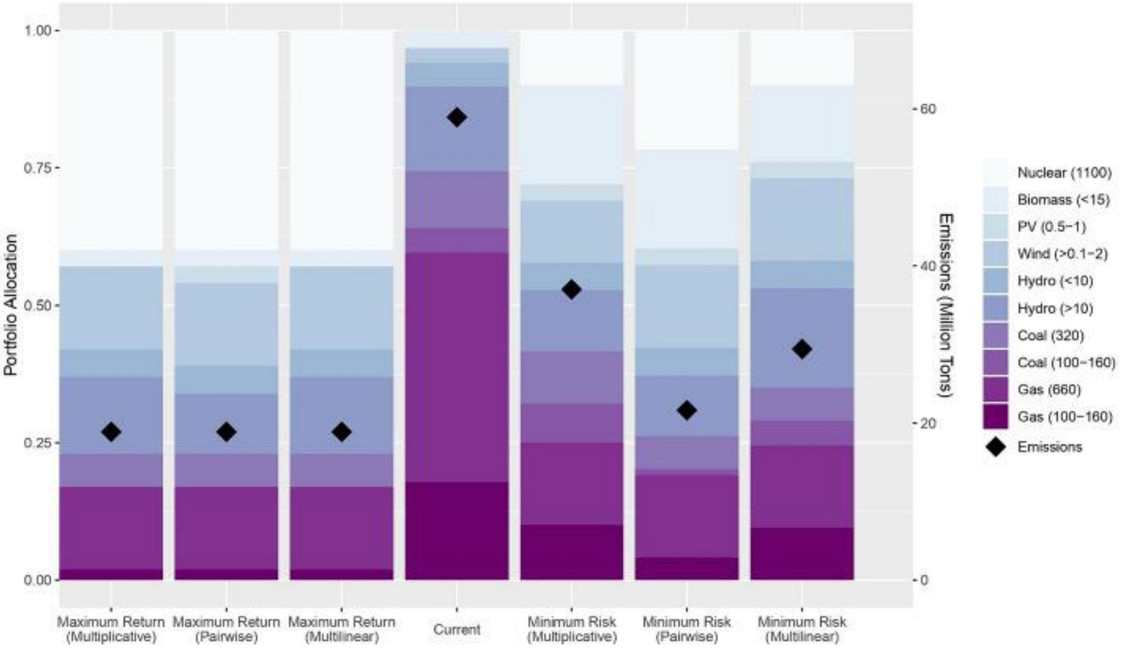

**Figure 4. Compromise Solutions in Comparison to Other Solutions Including the Nuclear Source**

The current Italian energy mix shows high $CO_2$ emissions and low renewable energy inclusion, with renewables contributing only 26% of electricity generation. Portfolios in Figures 3 and 4, based on interaction models like the multiplicative aggregation and dual compromise models, significantly reduce emissions and increase renewables. These models prioritize all sustainability variables equally rather than favoring economic factors, addressing policy goals more effectively. Compromise solutions are practical when variables score zero, offering flexibility despite data limitations. This review aids policymakers in managing sustainability complexities and optimizing energy technology use for a stronger, environmentally friendly energy framework.

## 3.3. Discussion of Results and Consequences for Policy

Priority should be given to secure, inexpensive and clean energy infrastructure by energy policies (Wu and Sansavini, 2021). In line with this, energy infrastructure should be broadened to all that are accessible while making sure that reliable energy supplies are consistently available. Priority should be given to investment in clean energy sources like wind, PV (solar) and thermal energy by countries, while making sure of accessibility to cost-effective electricity to the society (United Nations Transforming our world: the 2030 agenda for sustainable development (A/RES/70/1), 2015). At the frontline of long-term energy mix design and decisions should be sustainability, and as such that economic costs/benefits should not be the main focus, rather, the impact of diverse generation technologies on the environment and society should be given equal priority and importance.

Focus on the necessity for energy security and climate change mitigation had been the aim of researchers and professionals who have been working on developing a sustainable mix of energy generation technologies. Thus, in their evaluations, they have modeled the various sustainability dimensions. By adding the social and environmental costs estimates to the levelized cost of energy to obtain a sustainable generation mix have been proposed by earlier scholars (Li et al, 2024). Nevertheless, in designing a sustainable energy mix with this conventional approach, this method may not be effective in considering all the sustainability dimensions. This conventional approach places more importance on the economic dimension of sustainability that on the social and environmental variables of sustainability.

Greater flexibility would be needed in the optimization or modeling in order to expand the quota of renewable technologies in the generation mixes in agreement with deLlano-Paz (deLlano-Paz et al, 2017). For an equitable inclusion of all the sustainability variables in an optimal portfolio, the selected aggregation method to be used would be very important. The additive aggregation method of the cost variables would permit a low performance on some variables to be compensated by a high performance on others (Lo-Iacono-Ferreira et al, 2022). Furthermore, the difference in the weight of the estimates allotted to diverse cost attributes is usually large, hence, the additive aggregation method may not be effective in allocating renewable technologies equal opportunities to be selected or included in the energy mix as the non-renewable sources.

Multiplicative aggregation models conform better to the expectations of energy technology rankings than the additive model from the results of our review research. In the multiplicative aggregation models, there is a higher proportion of renewable energy sources included in the optimal portfolios in comparison to the additive model when the aggregate cost/returns and risks are subjected to portfolio optimization. For example, in Arnesano et al, 2012 optimal portfolios, there was recorded a total average of 43% (SD = 0.1870) renewable energy inclusion in the additive model, while the multiplicative aggregation model in the study derived an average of 57% (SD=0.0462) renewable energy inclusion in the optimal portfolio with no inclusion of the nuclear source.

The requirement for a well-adjusted and integrated technique to energy design and modeling that puts into consideration the equal significance of the three sustainability variables namely, social, economic and environmental dimensions is the focus of this research study. The interdependency among these sustainability dimensions if given priority attention in developing energy policies could result to the provision of a more secure, reliable and sustainable energy generation systems. It is of a critical importance that policy and decision makers when deciding on subsidies, regulations and incentives should give adequate consideration to all sustainability dimensions. The fundamental of the policy decision is to have all the sustainability dimensions effectively and adequately represented in the aggregated value, to this the policy and decision makers must give adequate attention to. Models should capture interactions among sustainability variables which promote a detailed and better knowledge and understanding of the performance of the technologies. This is what this review study advocates for and proposes. When such models are adopted by energy policies, the energy policy will be more consistent with sustainability objectives and provide more favorable outcomes and long standing benefits regarding the societal benefits, environmental impact and economic feasibilities of generation technologies. Flexible models that take into consideration data limitations are still beneficial to ensure that even when sufficient data is not available, decisions would still be informed and reliable.

## 4. Conclusion

This study investigated the impact of including social and environmental costs in the total generation cost for optimizing sustainable energy mix portfolios. It highlights improved methodologies for evaluating energy portfolio diversification, emphasizing the integration of economic, social, and environmental sustainability attributes. Traditional methods like the mean-variance approach have incorporated these variables but often rely on additive aggregation, which this study finds problematic. Additive models can disadvantage renewable energy sources when social and environmental factors are given equal importance to economic costs. In contrast, multiplicative aggregation models offer a more robust and accurate evaluation, capturing interactions among sustainability dimensions and better supporting renewable inclusion. The review also acknowledges limitations, focusing primarily on portfolio optimization and using the Italian energy mix data due to its comprehensive cost information. Challenges in risk data, especially for social costs, were noted, suggesting the need for further risk quantification. While the study sheds light on aggregation issues in energy mix design, it suggests that similar concerns may apply to other optimization and multi-criteria decision-making (MCDM) techniques, where limited attention has been given to aggregation impacts.

## References

Ahmadi, S. A., Mirlohi, S. M., Ahmadi, M. H., & Ameri, M. (2020). Portfolio optimization of power plants by using renewable energy in Iran. *International Journal of Low-Carbon Technologies, 16*(2), 463–475. https://doi.org/10.1093/ijlct/ctaa079

Allan, G., Eromenko, I., McGregor, P., & Swales, K. (2011). The regional electricity generation mix in Scotland: A portfolio selection approach incorporating marine technologies. *Energy Policy, 39*(1), 6–22. https://doi.org/10.1016/j.enpol.2010.08.028

Amin, G. R., & Hajjami, M. (2021). Improving DEA cross-efficiency optimization in portfolio selection. *Expert Systems with Applications, 168*, 114280. https://doi.org/10.1016/j.eswa.2020.114280

An, Q., Tao, X., Dai, B., & Xiong, B. (2020). Bounded-change target-setting approach: Selection of a realistic benchmarking path. *Journal of the Operational Research Society, 72*(3), 663–677. https://doi.org/10.1080/01605682.2019.1700185

Arnesano, M., Carlucci, A. P., & Laforgia, D. (2012). Extension of portfolio theory application to energy planning problem: The Italian case. *Energy, 39*(1), 112–124. https://doi.org/10.1016/j.energy.2011.06.053

Awerbuch, S., & Berger, M. (2003). Applying portfolio theory to EU electricity planning and policy making. *IEA/EET Working Paper, EET/2003/03*. https://scispace.com

Awerbuch, S., & Yang, S. (2007). Efficient electricity generating portfolios for Europe: Maximising energy security and climate change mitigation. *EIB Papers, 12*(2), 8–37. https://www.econstor.eu

Bar-Lev, D., & Katz, S. (1976). A portfolio approach to fossil fuel procurement in the electricity utility industry. *The Journal of Finance, 31*(3), 933–947. https://doi.org/10.2307/2326437

Basso, A., & Funari, S. (2001). A data envelopment analysis approach to measure the mutual fund performance. *European Journal of Operational Research, 135*(3), 477–492. https://doi.org/10.1016/S0377-2217(00)00311-8

Bhattacharya, A., & Kojima, S. (2012). Power sector investment risk and renewable energy: A Japanese case study using portfolio risk optimization method. *Energy Policy, 40*, 69–80. https://doi.org/10.1016/j.enpol.2010.09.031

Brandenburg, M., Govindan, K., Sarkis, J., & Seuring, S. (2014). Quantitative models for sustainable supply chain management: Developments and directions. *European Journal of Operational Research, 233*(2), 299–312. https://doi.org/10.1016/j.ejor.2013.09.032

Cabello, J. M., Navarro-Jurado, E., Rodríguez, B., Thiel-Ellul, D., & Ruiz, F. (2019). Dual weak–strong sustainability synthetic indicators using a double reference point scheme: The case of Andalucía, Spain. *Operational Research, 19*(3), 757–782. https://doi.org/10.1007/s12351-018-0390-5

Cinelli, M., Coles, S. R., & Kirwan, K. (2014). Analysis of the potentials of multi-criteria decision analysis methods to conduct sustainability assessment. *Ecological Indicators, 46*, 138–148. https://doi.org/10.1016/j.ecolind.2014.06.011

Delarue, E., De Jonghe, C., Belmans, R., & D'Haeseleer, W. (2011). Applying portfolio theory to the electricity sector: Energy versus power. *Energy Economics, 33*(1), 12–23. https://doi.org/10.1016/j.eneco.2010.05.003

deLlano-Paz, F., Calvo-Silvosa, A., Antelo, S. I., & Soares, I. (2017). Energy planning and modern portfolio theory: A review. *Renewable and Sustainable Energy Reviews, 77*, 636–651. https://doi.org/10.1016/j.rser.2017.04.045

Doukas, H., Karakosta, C., & Psarras, J. (2010). Computing with words to assess the sustainability of renewable energy options. *Expert Systems with Applications, 37*(7), 5491–5497. https://doi.org/10.1016/j.eswa.2010.02.061

Dyckhoff, H., & Allen, K. (2001). Measuring ecological efficiency with data envelopment analysis (DEA). *European Journal of Operational Research, 132*(2), 312–325. https://doi.org/10.1016/S0377-2217(00)00154-5

Dyer Maut, J. S. (2016). Multiattribute utility theory. In J. Figueira, S. Greco, & M. Ehrogott (Eds.), *Multiple criteria decision analysis* (pp. 285–314). Springer. https://doi.org/10.1007/978-1-4939-3094-4_8

Edirisinghe, N. C. P., & Zhang, X. (2007). Generalized DEA model of fundamental analysis and its application to portfolio optimization. *Journal of Banking & Finance, 31*(11), 3311–3335. https://doi.org/10.1016/j.jbankfin.2007.04.008

Elkington, J. (1998). *Cannibals with forks: The triple bottom line of 21st century business*. New Society Publishers.

Emrouznejad, A., & Yang, G. L. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Economic Planning Sciences, 61*, 4–8. https://doi.org/10.1016/j.seps.2017.01.008

Feng, C., & Wang, M. (2017). Analysis of energy efficiency and energy savings potential in China's provincial industrial sectors. *Journal of Cleaner Production, 164*, 1531–1541. https://doi.org/10.1016/j.jclepro.2017.07.081

Gan, G., Lee, H. S., Lee, L., Wang, X., & Wang, Q. (2019). Network hierarchical DEA with an application to international shipping industry in Taiwan. *Journal of the Operational Research Society, 71*(6), 991–1002. https://doi.org/10.1080/01605682.2019.1603792

Hacatoglu, K., Dincer, I., & Rosen, M. A. (2015). A new model to assess the environmental impact and sustainability of energy systems. *Journal of Cleaner Production, 103*, 211–218. https://doi.org/10.1016/j.jclepro.2014.06.050

Hacatoglu, K., Dincer, I., & Rosen, M. A. (2015). Sustainability assessment of a hybrid energy system with hydrogen-based storage. *International Journal of Hydrogen Energy, 40*(3), 1559–1568. https://doi.org/10.1016/j.ijhydene.2014.11.079

Hampf, B. (2014). Separating environmental efficiency into production and abatement efficiency: A nonparametric model with application to US power plants. *Journal of Productivity Analysis, 41*(3), 457–473.

Haugen, M., Blaisdell-Pijuan, P. L., Botterud, A., Levin, T., Zhou, Z., & Belsnes, M. (2024). Power market models for the clean energy transition: State of the art and future research needs. *Applied Energy, 357*, 122495. https://doi.org/10.1016/j.apenergy.2023.122495

Honma, S., & Hu, J. L. (2008). Total-factor energy efficiency of regions in Japan. *Energy Policy, 36*(2), 821–833. https://doi.org/10.1016/j.enpol.2007.10.026

Hu, J. L., & Wang, S. C. (2006). Total-factor energy efficiency of regions in China. *Energy Policy, 34*(17), 3206–3217. https://doi.org/10.1016/j.enpol.2005.06.015

Ioannou, A., Angus, A., & Brennan, F. (2017). Risk-based methods for sustainable energy system planning: A review. *Renewable and Sustainable Energy Reviews, 74*, 602–615. https://doi.org/10.1016/j.rser.2017.02.082

Keeney, R. L., & Raiffa, H. (1993). *Decisions with multiple objectives: Preferences and value tradeoffs*. Cambridge University Press.

Kim, Y. J., Cho, S. H., & Sharma, B. P. (2021). Constructing efficient portfolios of low-carbon technologies. *Renewable and Sustainable Energy Reviews, 150*, 111515. https://doi.org/10.1016/j.rser.2021.111515

Li, J., Gallego-Schmid, A., & Stamford, L. (2024). Integrated sustainability assessment of repurposing onshore abandoned wells for geothermal power generation. *Applied Energy, 359*. https://doi.org/10.1016/j.apenergy.2024.122670

Li, K., & Lin, B. Q. (2015). Metafrontier energy efficiency with $CO_2$ emissions and its convergence analysis for China. *Energy Economics, 48*, 230–241. https://doi.org/10.1016/j.eneco.2015.01.006

Lim, S., Oh, K. W., & Zhu, J. (2014). Use of DEA cross-efficiency evaluation in portfolio selection: An application to Korean stock market. *European Journal of Operational Research, 236*(1), 361–368. https://doi.org/10.1016/j.ejor.2013.12.002

Liu, W., Zhang, D. Q., Meng, W., Li, X. X., & Xu, F. (2011). A study of DEA models without explicit inputs. *Omega, 39*(5), 472–480. https://doi.org/10.1016/j.omega.2010.10.005

Lo-Iacono-Ferreira, V. G., Garcia-Bernabeu, A., Hilario-Caballero, A., & Torregrosa-López, J. (2022). Measuring urban sustainability performance through composite indicators for Spanish cities. *Journal of Cleaner Production, 359*, 131982. https://doi.org/10.1016/j.jclepro.2022.131982

Makridou, G., Andriosopoulos, K., Doumpos, M., & Zopounidis, C. (2016). Measuring the efficiency of energy-intensive industries across European countries. *Energy Policy, 88*, 573–583. https://doi.org/10.1016/j.enpol.2015.06.042

Malala, O. N., & Adachi, T. (2020). Portfolio optimization of electricity generating resources in Kenya. *The Electricity Journal, 33*(4), 106733. https://doi.org/10.1016/j.tej.2020.106733

Mari, C. (2014). Hedging electricity price volatility using nuclear power. *Applied Energy, 113*, 615–621. https://doi.org/10.1016/j.apenergy.2013.08.016

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7*(1), 77–91. https://doi.org/10.2307/2975974

Marrero, G. A., Puch, L. A., & Ramos-Real, F. J. (2015). Mean-variance portfolio methods for energy policy risk management. *International Review of Economics & Finance, 40*, 246–264. https://doi.org/10.1016/j.iref.2015.02.013

Mukherjee, K. (2008). Energy use efficiency in US manufacturing: A nonparametric analysis. *Energy Economics, 30*(1), 76–96. https://doi.org/10.1016/j.eneco.2006.11.004

Mukherjee, K. (2010). Measuring energy efficiency in the context of an emerging economy: The case of Indian manufacturing. *European Journal of Operational Research, 201*(3), 933–941. https://doi.org/10.1016/j.ejor.2009.04.012

Novacheck, J., & Johnson, J. X. (2017). Diversifying wind power in real power systems. *Renewable Energy, 106*, 177–185. https://doi.org/10.1016/j.renene.2016.12.100

Park, S. Y., Yun, B.-Y., Yun, C. Y., Lee, D. H., & Choi, D. G. (2016). An analysis of the optimum renewable energy portfolio using the bottom–up model: Focusing on the electricity generation sector in South Korea. *Renewable and Sustainable Energy Reviews, 53*, 319–329. https://doi.org/10.1016/j.rser.2015.08.029

Pomerol, J. C., & Barba-Romero, S. (2000). Multicriterion decision in management: Principles and practice. Springer.

López Prol, J., de Llano Paz, F., Calvo Silvosa, A., Pfenninger, S., & Staffell, I. (2024). Wind-solar technological, spatial and temporal complementarities in Europe: A portfolio approach. *Energy, 292*, 130348. https://doi.org/10.1016/j.energy.2024.130348

Ramanathan, R. (2006). Evaluating the comparative performance of countries of the Middle East and North Africa: A DEA application. *Socio-Economic Planning Sciences, 40*(2), 156–167. https://doi.org/10.1016/j.seps.2004.10.002

Rombauts, Y., Delarue, E., & D'haeseleer, W. (2011). Optimal portfolio-theory-based allocation of wind power: Taking into account cross-border transmission-capacity constraints. *Renewable Energy, 36*(9), 2374–2387. https://doi.org/10.1016/j.renene.2011.02.010

Roques, F., Hiroux, C., & Saguan, M. (2010). Optimal wind power deployment in Europe—a portfolio approach. *Energy Policy, 38*(7), 3245–3256. https://doi.org/10.1016/j.enpol.2009.07.048

Rowley, H. V., Peters, G. M., Lundie, S., & Moore, S. J. (2012). Aggregating sustainability indicators: Beyond the weighted sum. *Journal of Environmental Management, 111*, 24–33. https://doi.org/10.1016/j.jenvman.2012.05.004

Santos-Alamillos, F. J., Thomaidis, N. S., Usaola-García, J., Ruiz-Arias, J. A., & Pozo-Vázquez, D. (2017). Exploring the mean-variance portfolio optimization approach for planning wind repowering actions in Spain. *Renewable Energy, 106*, 335–342. https://doi.org/10.1016/j.renene.2017.01.041

Shakouri, M., Lee, H. W., & Choi, K. (2015). PACPIM: New decision-support model of optimized portfolio analysis for community-based photovoltaic investment. *Applied Energy, 156*, 607–617. https://doi.org/10.1016/j.apenergy.2015.07.060

Simar, L., & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science, 44*(1), 49–61. https://doi.org/10.1287/mnsc.44.1.49

Simar, L., & Wilson, P. W. (2000). A general methodology for bootstrapping in non-parametric frontier models. *Journal of Applied Statistics, 27*(6), 779–802. https://doi.org/10.1080/02664760050081951

Simoglou, C. K., Biskas, P. N., Marneris, I. G., & Roumkos, C. G. (2022). Long-term electricity procurement portfolio optimization. *Electric Power Systems Research, 202*, 107582. https://doi.org/10.1016/j.epsr.2021.107582

Stempien, J. P., & Chan, S. H. (2017). Addressing energy trilemma via the modified Markowitz mean-variance portfolio optimization theory. *Applied Energy, 202*, 228–237. https://doi.org/10.1016/j.apenergy.2017.05.145

Stewart, T. J. (2005). Dealing with uncertainties in MCDA. In J. Figueira, S. Greco, & M. Ehrogott (Eds.), *Multiple criteria decision analysis: State of the art surveys* (pp. 445–466). Springer. https://doi.org/10.1007/0-387-23081-5_11

Sykes, J. P., & Trench, A. (2014). Finding the copper mine of the 21st century: Conceptual exploration targeting for hypothetical copper reserves. *Society of Economic Geologists, Inc. Special Publication, 18*, 273–300. https://doi.org/10.5382/SP.18.14

Tao, et al. (2020). Energy efficiency evaluation based on data envelopment analysis: A literature review. *Energies, 13*(14), 3548. https://doi.org/10.3390/en13143548

Tarnaud, A. C., & Leleu, H. (2018). Portfolio analysis with DEA: Prior to choosing a model. *Omega, 75*, 57–76. https://doi.org/10.1016/j.omega.2017.02.003

Thies, C., Kieckhäfer, K., Spengler, T. S., & Sodhi, M. S. (2019). Operations research for sustainability assessment of products: A review. *European Journal of Operational Research, 274*(1), 1–21. https://doi.org/10.1016/j.ejor.2018.04.039

Turkson, C., Acquaye, A., Liu, W., & Papadopoulos, T. (2020). Sustainability assessment of energy production: A critical review of methods, measures and issues. *Journal of Environmental Management, 264*, 110464. https://doi.org/10.1016/j.jenvman.2020.110464

United Nations. (2015). *Transforming our world: The 2030 agenda for sustainable development (A/RES/70/1)*. https://sustainabledevelopment.un.org/content/documents/21252030%20Agenda%20for%20Sustainable%20Development%20web.pdf

Von Neumann, J., & Morgenstern, O. (1947). *Theory of games and economic behavior* (2nd ed.). Princeton University Press.

Wang, J. J., Jing, Y. Y., Zhang, C. F., & Zhao, J. H. (2009). Review on multi-criteria decision analysis aid in sustainable energy decision-making. *Renewable and Sustainable Energy Reviews, 13*(9), 2263–2278. https://doi.org/10.1016/j.rser.2009.06.021

Wang, Z. H., Zeng, H. L., Wei, Y. M., & Zhang, Y. X. (2012). Regional total factor energy efficiency: An empirical analysis of industrial sector in China. *Applied Energy, 97*, 115–123. https://doi.org/10.1016/j.apenergy.2011.12.071

Wang, K., Wei, Y. M., & Huang, Z. (2018). Environmental efficiency and abatement efficiency measurements of China's thermal power industry: A data envelopment analysis based materials balance approach. *European Journal of Operational Research, 269*(1), 35–50. https://doi.org/10.1016/j.ejor.2017.04.053

Welch, E., & Barnum, D. (2009). Joint environmental and cost efficiency analysis of electricity generation. *Ecological Economics, 68*(8–9), 2336–2343. https://doi.org/10.1016/j.ecolecon.2009.03.004

Westner, G., & Madlener, R. (2010). The benefit of regional diversification of cogeneration investments in Europe: A mean-variance portfolio analysis. *Energy Policy, 38*(12), 7911–7920. https://doi.org/10.1016/j.enpol.2010.09.011

Westner, G., & Madlener, R. (2011). Development of cogeneration in Germany: A mean-variance portfolio analysis of individual technology's prospects in view of the new regulatory framework. *Energy, 36*(8), 5301–5313. https://doi.org/10.1016/j.energy.2011.06.038

Wu, J., Yin, P. Z., Sun, J. S., Chu, J. F., & Liang, L. (2016). Evaluating the environmental efficiency of a two-stage system with undesired outputs by a DEA approach: An interest preference perspective. *European Journal of Operational Research, 254*(3), 1047–1062. https://doi.org/10.1016/j.ejor.2016.04.034

Wu, J., Xiong, B., An, Q., Sun, J., & Wu, H. (2017). Total-factor energy efficiency evaluation of Chinese industry by using two-stage DEA model with shared inputs. *Annals of Operations Research, 255*(1–2), 257–276. https://link.springer.com

Wu, R., & Sansavini, G. (2021). Energy trilemma in active distribution network design: Balancing affordability, sustainability and security in optimization-based decision-making. *Applied Energy, 304*, 117891. https://doi.org/10.1016/j.apenergy.2021.117891

Yang, G., Shen, W., Zhang, D., & Liu, W. (2014). Extended utility and DEA models without explicit input. *Journal of the Operational Research Society, 65*(8), 1212–1220. https://doi.org/10.1057/jors.2013.68

Zhang, N., Kong, F., & Yu, Y. (2015). Measuring ecological total-factor energy efficiency incorporating regional heterogeneities in China. *Ecological Indicators, 51*, 165–172. https://doi.org/10.1016/j.ecolind.2014.07.041

Zhang, Y. J., Sun, Y. F., & Huang, J. (2018). Energy efficiency, carbon emission performance, and technology gaps: Evidence from CDM project investment. *Energy Policy, 115*, 119–130. https://doi.org/10.1016/j.enpol.2017.12.056

Zhang, N., & Choi, Y. (2013). Environmental energy efficiency of China's regional economies: A non-oriented slacks-based measure analysis. *The Social Science Journal, 50*(2), 225–234. https://doi.org/10.1016/j.soscij.2013.01.003

Zhang, Z. (2003). Why did the energy intensity fall in China's industrial sector in the 1990s? The relative importance of structural change and intensity change. *Energy Economics, 25*(6), 625–638. https://doi.org/10.1016/S0140-9883(03)00042-2

Zhao, H., Guo, S., & Zhao, H. (2019). Provincial energy efficiency of China quantified by three-stage data envelopment analysis. *Energy, 166*, 96–107. https://doi.org/10.1016/j.energy.2018.10.063

Zhou, P., Ang, B. W., & Poh, K. L. (2008). A survey of data envelopment analysis in energy and environmental studies. *European Journal of Operational Research, 189*(1), 1–18. https://doi.org/10.1016/j.ejor.2007.04.042

Zhou, Z., Xiao, H., Jin, Q., & Liu, W. (2018). DEA frontier improvement and portfolio rebalancing: An application of China mutual funds on considering sustainability information disclosure. *European Journal of Operational Research, 269*(1), 111–131. https://doi.org/10.1016/j.ejor.2017.07.010

Zhou, H., Yang, Y., Chen, Y., & Zhu, J. (2018). Data envelopment analysis application in sustainability: The origins, development and future directions. *European Journal of Operational Research, 264*(1), 1–16. https://doi.org/10.1016/j.ejor.2017.06.023

Zhou, P., & Ang, B. W. (2008). Linear programming models for measuring economy-wide energy efficiency performance. *Energy Policy, 36*(8), 2911–2916. https://doi.org/10.1016/j.enpol.2008.03.041

Zhu, Z., Wang, K., & Zhang, B. (2014). Applying a network data envelopment analysis model to quantify the eco-efficiency of products: A case study of pesticides. *Journal of Cleaner Production, 69*, 67–73. https://doi.org/10.1016/j.jclepro.2014.01.064

Zhu, L., & Fan, Y. (2010). Optimization of China's generating portfolio and policy implications based on portfolio theory. *Energy, 35*(3), 1391–1402. https://doi.org/10.1016/j.energy.2009.11.024