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A data envelopment analysis based evaluation of sustainable energy generation portfolio scenarios

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HIGHLIGHTS

- Sustainable energy mix literature relies on the additive aggregation of costs.
- Additive aggregation allows compensation across sustainability dimensions.
- We examine various cost aggregation methods.
- Various optimization models are developed to test aggregation methods
- More sustainable portfolios are generated through multiplicative aggregation.

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ABSTRACT

Generating secure, affordable, and clean energy requires careful evaluation of the costs and associated risks of different energy generation sources. Portfolio optimisation models are commonly used in this regard to help diversify risks associated with generation sources. In recent times, energy policies often require the consideration of the environmental and social effects of such activity. Consequently, sustainability has become a key factor in making energy mix planning decisions. To incorporate sustainability considerations in energy mix planning, the conventional approach has been to add indicators for environmental and social costs to the total generation cost for each available technology in a portfolio optimisation model. However, this approach to developing a sustainable generation mix may not effectively address all dimensions of sustainability. In most cases, the economic dimension is prioritised over social and environmental factors. We examine how various aggregation methods impact the preference among the sources and the optimal portfolio mix and propose aggregation methods that effectively incorporate all sustainability dimensions. We observed that technology ranking based on multiplicative, pairwise interaction, and multilinear aggregation options aligns better with our sustainability goals than additive aggregation. By adopting these methods of aggregation, we were able to include more renewable and clean energy sources in our optimal portfolios.

1. Introduction

Rapid economic development and increasing population growth globally have put pressure on energy resources [56]. As such, the development and planning of energy generation sources have become a matter of priority for countries. However, due to awareness of the limits of non-renewable primary resources, environmental and social impacts of both renewable and non-renewable generation sources and increasing requirements of policy for clean, secure and affordable energy (the energy trilemma) [54], there is a growing research interest in constructing a sustainable mix of energy generation technologies/sources. Energy generation mix and power flow planning is an important area of research because of the urgency to decarbonise by deploying low-carbon infrastructure [20] in line with the requirement to achieve goal seven of the UN Sustainable Development Goals (SDGs): “Ensure access to affordable, reliable, sustainable and modern energy for all” [49].

In response to this research and policy interest, different methods have been employed in the interest of constructing a diversified mix of energy generation sources that meet the energy demand requirements of

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Nomenclature

CCR	Charnes, Cooper, and Rhodes (*i.e.* Constant Returns to Scale)
DEA	Data Envelopment Analysis
kWh	Kilowatt-hour
MCDM	Multi-Criteria Decision Making
O&M	Operation and Maintenance
PV	Photovoltaic
WEI	Without Explicit Output (*i.e.* index data form)
$E(R_p)$	The expected annual value/return of a portfolio p
$E(r_j)$	The expected return of technology j
$E(r_{rj})$	The expected return of sustainability dimension r for technology j
σ_p	Standard deviation of a portfolio p
σ_j	Standard deviation (risk) of a technology j
σ_{rj}	Standard deviation (risk) of sustainability dimension r for a technology j
ρ_{jk}	Correlation between technology j and technology k
w_j	Weight of technology j
$u(Y)$	Utility of a set of Y mutually utility independent attributes
ϕ	A risk-adjusted performance measure
z_j	A non-negative vector of weights for technology j

a country while managing the associated risks to the environment and society. Ioannou et al. [21], reviewed the risk-based methods for sustainable energy system planning and observed that optimisation methods, the mean-variance portfolio theory and multi-criteria decision analysis are the prominent techniques for the construction and analysis of sustainable generation portfolios. For the mean-variance framework, the early work of Bar-Lev and Katz [6] and later Awerbuch and Berger [4] established the foundation for applying portfolio diversification theory to energy planning decisions to optimise the portfolio of generation technologies. At its foundation, the method requires estimates for generation cost and risks as the building blocks for assessment. While these early works did not have sustainability considerations as a primary objective, later works have sought to develop a sustainable mix of generation sources that considers the policy needs for energy security and climate change mitigation.

The sustainability problem requires the modelling of the different dimensions of sustainability - economic, social, and environmental dimensions [9,24]. The solution adopted in energy mix planning studies is to add environmental and other social costs to the generation cost and risks used in the optimisation model [8,32]. Arnesano et al. [3], for example, defined total generation cost to be the sum of industrial, external, and direct and indirect CO_2 costs. While the industrial cost component comprised construction, fuel and operation and maintenance (O&M) costs per kWh, the external and CO_2 cost components captured the social and environmental impacts of the various generation technologies. Marrero et al. [32], added the externality cost of CO_2 emissions to the levelized cost of energy in the sensitivity analysis to model the potential complementarity between renewable and non-renewable energy sources in reducing both portfolio risk/cost and CO_2 emission.

While this approach for incorporating the social and/or environmental costs in the portfolio diversification problem is widely accepted in sustainable energy mix planning, we argue that this is not adequately effective in modelling the relevance of these sustainability dimensions in such problems. This is because adding such environmental and societal costs to other economic generation costs does not capture the preference relationship between the dimensions. By relying on multi-attribute utility theory, and data envelopment analysis (DEA), it is shown that the preference relationships in an additive model fail to consider the joint effects in such multiple dimension aggregation problems. This has implications for the optimal portfolios generated and the emissions reduction potential. For additive aggregation, there is a greater potential for poor performance on some dimensions of sustainability to be compensated by good performance on other dimensions of sustainability [10,27]. Additionally, the large differences in the magnitude of the contributions of each of the cost dimensions towards total generation cost mean some dimensions may be disadvantaged in favour of dimensions with higher contribution magnitude. In the Arnesano et al. [3] case, for example, the social and environmental dimensions on average accounted for only 18% of the total generation cost of a technology, while the industrial (economic) cost accounted for 82% of the total cost. Therefore, the portfolios generated in such assessment overly advantage the economic dimension of sustainability to the disadvantage of the other equally important sustainability dimensions. Hence there is more emission-reduction potential for a truly sustainable energy portfolio diversification if the preferences and magnitudes of these dimensions are more effectively modelled.

The need to ensure sustainability, security and affordability of energy is one of the most pressing concerns faced by many governments and international bodies in contemporary times. As such, effective modelling of the problem is key for energy policy. This paper examines the impact of the composition of the cost structure on the preference between alternative generation sources that should be optimised in a portfolio model. As such, the implications of various cost configurations on the preference between sources and the optimal portfolio of sources are presented to show the weaknesses of traditional approaches to constructing sustainable generation mixes. From this, recommendations are made on how to generate a more sustainable mix with higher emissions reduction potential and a more effective combination of renewable and non-renewable generation sources. This paper contributes to the existing literature by highlighting the limitations of traditional approaches in incorporating environmental and social costs into the portfolio diversification problem. This introduces a novel perspective by integrating multi-attribute utility theory and DEA to better understand the joint effects of these dimensions and address the shortcomings of additive aggregation. In this regard, novel DEA models are developed to study the implications of aggregation technique on the ranking of sources. We identify and discuss the weaknesses in traditional methods of constructing sustainable generation mixes. This critical analysis is important for informing policy makers and researchers about the potential biases in existing models, and therefore urging for a more balanced and comprehensive approach. Finally, we also provide recommendations for generating a more sustainable energy mix with higher emissions reduction potential.

To achieve these objectives, the remainder of the paper is organised as follows: Section 2 presents a review of previous literature. Section 3 is the methodology section. We formulate various optimisation models to examine the relationship between the dimensions of sustainability. Section 4 presents an empirical analysis. In this section, we first examine the impact of various configurations of cost composition on rankings of individual sources using DEA. This is then followed by the impact of the cost configuration on the optimal portfolio selected using the mean-variance framework. Finally, concluding remarks and recommendations are made in Section 5.

2. Previous work

Markowitz [31], first introduced a mean-variance framework for optimising a portfolio of investment assets by maximising expected returns and minimising associated risks. Since then, this mean-variance framework has found relevance in several areas, including energy planning decisions. Bar-Lev and Katz [6] and Awerbuch and Berger [4] were the early works that advocated for the application of this portfolio diversification theory in energy planning decisions to optimise the portfolio of generation technologies. Subsequently, there have been many other studies that have used the mean-variance framework in energy planning decisions [1,29,43]. Although there have been several approaches and applications of the mean-variance framework in energy portfolio planning [53], at its foundation, the framework requires estimates for generation cost (or return) and risk, which form the building blocks for further assessment. The composition of the generation cost (or return) and risk have been the basis for some differences in literature since it has direct implications on the nature of optimal portfolios generated.

On the one hand, some studies tackle portfolio optimisation problems without considering negative externalities borne by the environment and society [2,12,40]. For example, the components of the generation cost in Delarue et al. [12] include investment costs, fuel costs and fixed and variable O&M costs. Similarly, Allan et al. [2] considered private costs in estimating the levelized costs of the technology, thereby ignoring external costs such as the cost of emissions. Cost components considered included construction, storage, fuel and fuel delivery, pre-development, O&M costs and a waste and processing plant decommissioning cost for nuclear energy [2]. Studies that do not consider environmental or societal dimensions provide portfolios aimed at optimising the generation cost in ensuring secure and affordable energy. However, such studies ignore the requirement for clean energy, which is an essential part of the sustainable energy policy. As such, optimal portfolios generated do not factor in emission-reduction potential, thereby, favouring non-renewable sources compared to renewable generation sources.

On the other hand, some studies include environmental or external impacts when estimating expected generation cost or return [33,44]. The ambitious carbon emissions reduction targets and the need to raise energy efficiency has significantly influenced the structure of power generation [52,53]. Consequently, some studies have sort to consider the seemingly conflicting and competing priorities of energy security and sustainability/climate change policies [44]. Existing literature incorporate these sustainability concerns by adding cost indicators from environmental and societal dimensions to the generation costs which are used in the earlier instances. For example, in the case of Zhu and Fan [59], their optimisation of China's generation portfolio used a summation of generating costs (combining investment, fuel and O&M costs) and CO_2 costs in their evaluation. Similarly, Arnesano et al. [3], defined a total cost as a sum of costs from the economic, environmental and social dimensions of sustainability. These studies follow the approach by Awerbuch and Yang [5] who included the expected market price of carbon emissions into the total cost in their evaluation. However, in such instances, these other environmental and social cost components, account for substantially lower proportion of the total cost. This is because, with additive aggregation an important dimension can be compensated by other dimensions. As such, the true effect of the environmental and social dimensions may not be observed in the optimal portfolios generated.

There are others who focus on only renewable energy sources in their portfolio diversification problem. For example, López Prol et al. [28], constructed optimal portfolios comprising of wind and solar sources in the European context. However, in practice, the energy mix of nations comprises both renewable and non-renewable sources. Consequently, limiting the sources considered to only renewable sources limits the applicability of the results by policymakers. Finally, the others who use portfolio theory in energy mix problems. However, their evaluation is focussed on a private investor's stock selection problem rather than a country's energy mix problem. An example of such a study is Kuang [23] who examined whether clean energy stocks are attractive in stock selection. Such private investor problems are not considered in this paper.

3. Methodology

3.1. Portfolio diversification

The mean-variance framework of Markowitz [31] used in portfolio optimisation requires estimates of the expected value of the portfolio of generation sources and associated risk. The portfolio expected return is defined from the generation cost [30,34] or output perspectives [37]. In energy mix planning, however, the inverse of the expected generation cost is usually used in a maximisation model [12]. The general portfolio expected return is defined as [37]:

$$E(R_p) = \sum_{j=1}^{n} w_j E(R_j) \tag{1}$$

This expected annual value of the portfolio $E(R_p)$ comprises the weighted sum of the returns of n technologies under investigation. The risk of the portfolio is estimated by the standard deviation of the technologies:

$$\sigma_p = \left(\sum_{j=1}^{n} w_j^2 \sigma_j^2 + \sum_{j=1}^{n} \sum_{\substack{k=1 \\ j \neq k}}^{n} w_j w_k \sigma_j \sigma_k \rho_{jk} \right)^{\frac{1}{2}} \tag{2}$$

Where the σ_j and σ_k represent the standard deviation of technology j and technology k, while ρ_{jk} is the correlation between technology j and k. In the optimisation problem, the portfolio with the highest return can be found by maximising the portfolio expected return subject to the portfolio risk as a constraint. On the other hand, the minimum-variance portfolio can be estimated by minimising the portfolio risk subject to the expected return as a constraint. For both problems, there is a further requirement for the weights w_j to sum up to unity, such that: $\sum_{j=1}^{n} w_j = 1$. There may be other upper and lower bound requirements, as well as capacity constraints on the optimal weights to be estimated. This depends on the national and international policies on the generation mix [36,39].

3.2. Decomposing the expected return and risk

The focus of this paper is to examine the internal structure of the return of technology from which the optimal portfolio is selected. The expected return, defined from the inverse of generation costs, comprises various generation cost types including (but not limited to) O&M costs, capital/investment cost, fuel costs, as well as emissions factor usually from carbon trading, as well as external costs such as costs on health damages [12]. These costs may be generally classified as private industrial costs incurred during the plant operation and CO_2 costs usually imposed by governments to check emissions and external costs that could be incurred as a result of the impact of the operation of the plant on society [2,3]. Total cost should reflect the economic, social, and environmental costs per unit of energy produced which should be minimised to achieve secure, affordable and clean energy. Consequently, the generation cost (and the risk) of technology is the basis for determining preference between different generation sources to generate a sustainable mix.

The total cost is often defined as a sum or weighted sum of the various cost components for each technology (see [3,12]). If the cost of generation is decomposed into the r independent sustainability dimensions (*i.e.* economic, social and environmental dimensions), the expected return and variance of a given technology j can be defined as:

$$E(R_j) = \sum_{r=1}^{s} E(r_r) \tag{3}$$

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

where $r_r = 1/c_r$. The covariance is zero since the components are independent. Summing the components may not provide a truly sustainable portfolio since disadvantages on some dimensions can be compensated by large advantages on other dimensions. Since the expected return is the basis for determining the overall sustainability and preference between technologies, it is possible to look at the problem from a utility maximisation perspective. If the preference between alternatives satisfy the Von Neumann and Morgenstern [50] axioms of rational behaviour and the components are mutually utility independent, then it is possible to express the multi-attribute utility problem in multilinear form [22,45]:

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

where k's are scaling constants that ensure consistency. The attribute y_r is utility independent of its complements if the preference for lotteries with different levels of that attribute y_r does not depend on fixed levels of the remaining attributes [45]. In this case, higher economic returns are preferred to low economic returns at the same level of social and environmental returns. If all subsets of all attributes are utility independent of their complements, then the attributes are mutually utility independent [22,45]. The multilinear form is a generalisation of both the additive and multiplicative utility functions [22]. The additive expected return as expressed in follows the first term of the multilinear utility model in (5). Additive aggregation is used if alternatives satisfy additive independence, meaning preferences between the lotteries depend only on the marginal probability distributions [22]. It ignores the joint probability distribution and hence does not allow for interaction between the attributes. Elkington [17] shows sustainability as the point of intersection between social (people), environmental (planet) and economic (profit) objectives. Therefore, the idea of sustainability-focused planning decisions should require *both* economic efficiency and external considerations not *either* economic *or* external. This is seen in the triple bottom line framework, which shows sustainability as the point of intersection between economic, social, and environmental dimensions.

An approach that constructs composite scores in a way that allows disadvantages on some criteria to be offset by large advantages on other criteria [18,19,38] is inconsistent with the idea of sustainability [17]. Additivity of the utility function across attributes with comparable scales allows for loss on one criterion to be compensated by gains of another [35]. Additionally, the various dimensions may not have the same magnitude. Bhattacharya and Kojima [8], for instance, show that CO_2 costs represent very little of the total generating cost breakdown in the Japanese case with economic costs (capital, fuel and O&M) accounting for about 75% of the total risk. Awerbuch and Yang [5], showed that carbon costs play very little in the generating cost structure of fossil-based fuels and even no direct impact on the cost of generating non-fossil technologies. Examining these dimensions by the sum of the costs has the potential of reducing the weight of CO_2 and other external costs in the final analysis and so goes contrary to the ideals of sustainability.

In the case of sustainability, it may be more appropriate to define the expected return of the technology as a product of the dimensions. In that case, the joint probability distribution across dimensions is of concern such that overall preference for a technology differs at different levels of some dimensions. Consequently, the desirability of different amounts of a dimension may depend on the specific level of other dimensions [22]. Such interaction is not captured in the additive utility function. In such a case, the multiplicative preference relation may be preferred for determining the expected return of technology across the sustainability dimensions. This presents some complexity in the estimation of the risk attributable to the various components. When variables are interacting, variance depends on whether the interacting variables are independent random variables or are correlated. Since the economic, social and environmental cost components are independent, the covariance between the components is assumed to be zero.

$$E(R_j) = \prod_{r=1}^{s} E(r_r) \tag{6}$$

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

Although the multilinear function in (5) has different levels of interactions between the dimensions, since the definition of sustainability requires all three dimensions, this study focuses on the interaction between all three dimensions in determining the technology return. However, it may sometimes be useful to rely on pairwise interaction when technology has zero costs/returns on some dimensions. In the next section, optimisation models to examine the different relationships between dimensions of sustainability are developed. These models are empirically tested in later sections to see how the relationship between dimensions influences the preference between technologies.

3.3. Modelling the relationship between sustainability dimensions

DEA is the multi-criteria decision-making (MCDM) technique used as the basis for evaluating the impact of various cost configurations on the scores and rankings of the technologies. Multi-criteria decision-making approaches have been widely used and advanced methodologically to incorporate multiple dimensions and indicators in sustainability research [14,48]. DEA has an advantage over other MCDM approaches as it does not have challenges with normalisation, dimension weighting and aggregation when incorporating economic, social and environmental impacts as occurs with other MCDM approaches [11,51]. With DEA, it is possible to examine the dimensions from the individual to the composite levels which allows for the examination of the impact of the dimension configuration on the composite scores. Advances in DEA allow for the examination of different preferences. Additionally, DEA has been widely used for portfolio optimisation problems [7,16,26,58] and sustainability assessment of various nature [47,57].

3.3.1. Relationship between DEA and multilinear utility function

The multilinear utility function is presented in eq. (5), with a set of $Y = (y_1, y_2, \ldots, y_s)$ mutually utility independent attributes. Here $u_r(y_r)$ is the utility function of the rth attribute scaled by k_r where $0 \le k_r \le 1$. In practice, the procedure for constructing the utility $u(Y)$ in multi-attribute utility theory, involves first assessment of the partial utilities $u_r(y_r)$ then determining appropriate scaling using qualitative judgements, and other approaches like Analytic Hierarchy Process, Entropy method or Principal Component Analysis [15,55]. Yang et al. [55] have shown the relationship between the DEA approach and the multi-attribute utility theory in estimating the scaling factors. Since the attributes in (5) are all 'more is better', DEA Without Explicit Output (DEA-WEI), which uses index data of the form $y_{ir} = e_r/x_i$ where e_r and x_i are outputs and inputs respectively [25], can be used for the assessment of the scaling factors [55] in the quadratic model:

$$\begin{aligned}
h = Max &\sum_{r=1}^{s} w_r u_r(y_{ro}) + \sum_{r=1}^{s} \sum_{t>r} w_{rt} u_r(y_{ro}) u_t(y_{to}) + \ldots + w_{1,2,\ldots,s} u_1(y_{1o}) u_2(y_{2o}) \ldots u_s(y_{so}) \\
\text{s.t.} &\sum_{r=1}^{s} w_r u_r(y_{rj}) + \sum_{r=1}^{s} \sum_{t>r} w_{rt} u_r(y_{rj}) u_t(y_{tj}) + \ldots + w_{1,2,\ldots,s} u_1(y_{1j}) u_2(y_{2j}) \ldots u_s(y_{sj}) \le 1 \\
&w_r \ge 0, j = 1, \ldots, n, r = 1, \ldots, s, t = 1, \ldots, s
\end{aligned} \tag{8}$$

The objective in (8) determines the scaling factors that maximise the multilinear utility function of the alternative o under investigation subject to the restriction that for all the other j alternatives ($j = 1,\ldots, n$), the same function given the chosen scaling factors does not exceed unity. Alternatively, the dual form of the linear programming problem (8) may be preferred:

$$\begin{aligned} & Max \quad \theta \\ & \text{s.t.} \quad \sum_{j=1}^{n} z_j u_r(y_{rj}) \geq \theta u_r(y_{ro}), r = 1,\ldots,s \\ & \qquad \sum_{j=1}^{n} z_j u_r(y_{rj}) u_t(y_{tj}) \geq \theta u_r(y_{ro}) u_t(y_{to}), r = 1,\ldots,s, t = 1,\ldots,s \\ & \qquad \vdots \\ & \qquad \sum_{j=1}^{n} z_j u_1(y_{1j}) u_2(y_{2j}) \ldots u_s(y_{sj}) \geq \theta u_1(y_{1o}) u_2(y_{2o}) \ldots u_s(y_{so}) \\ & \qquad \sum_{j=1}^{n} z_j = 1 \\ & \qquad \theta \geq 1 \\ & \qquad z_j \geq 0, j = 1,\ldots,n \end{aligned} \tag{9}$$

The optimal solution of (9) is the reciprocal of the optimal solution of (8). In a single input case, as in the risk-return problem, the DEA-WEI can directly be converted into the constant returns to scale DEA model [25]:

$$\begin{aligned} & Max \quad \theta \\ & \text{s.t.} \quad \sum_{j=1}^{n} \lambda_j e_{rj} \geq \theta e_{ro} \\ & \qquad \sum_{j=1}^{n} \lambda_j x_j \leq x_o \\ & \qquad \lambda_j \geq 0, j = 1,\ldots,n, r = 1,\ldots,s \end{aligned} \tag{10}$$

Note that (10), shows the CCR model corresponding to a DEA-WEI model with just the additive term in the multilinear function. It is possible to show a CCR model with the interacting terms. This will only require additional constraints. In the next sub-section, DEA models based on the CCR are developed to examine how the relationship between the sustainability dimensions influence the rankings of technologies.

3.3.2. DEA modelling of attribute relationships

DEA models using the CCR model to examine how the modelling of the relationship between the sustainability dimensions (or attributes) influence the ordinal ranking of the technologies ($j = 1,\ldots,n$). In this section, the expected return $(E(r))$ is modelled as the output to be maximised while the risk (σ) is modelled as the input to be minimised. For each of the DEA models to be presented, the score may be interpreted as a risk-adjusted performance measure since returns are maximised at given levels of risks.

3.3.2.1. Additive modelling of sustainability dimensions (Model 1). As a starting point, the DEA model with expected return and risk defined by (3) and (4) is presented for the performance ranking. This model uses technology returns as a sum of the returns of the various sustainability dimensions that make up the generation cost of the technology. This risk measure in (11) is the square root of the variance in (4). This is the traditional way return is estimated for the portfolio optimisation problems.

$$\begin{aligned} & E_o^1 = \max_{z,\phi} \quad \phi \\ & \text{s.t.} \quad \sum_{j=1}^{n} z_j \sigma_j \leq \sigma_o \\ & \qquad \sum_{j=1}^{n} z_j E(r_j) \geq E(r_o)\phi \\ & \qquad z_j \geq 0, j = 1,2,\ldots,n \end{aligned} \tag{11}$$

For technology o, the objective is to find the maximum Pareto-efficient proportional expansion in expected return, given its risk level. As such, if the score ϕ is equal to unity, then there is no opportunity for expansion of return since no other technology has a more Pareto-efficient risk-return combination. The inverse of the score in (11) is bounded by zero and unity with unity as the most efficient score $\left(0 < \frac{1}{\phi} \leq 1\right)$. Also, z_j is a non-negative vector of weights for technology j and $E(r_j)$ is the additive expected return score for technology j. The model formulated assumes constant returns to scale (hereafter called CCR) since it has better discriminatory power. It is believed that the rankings in (11) are inconsistent with the idea of sustainability since the various dimensions are combined without the requirement for good performance on each of the sustainability dimensions, therefore, allowing compensation.

3.3.2.2. Separating the sustainability dimensions (Model 2). To address the weakness of the additive model presented in (11), one solution may be to define the various dimensions as separate outputs thereby allowing Pareto preference on each of the sustainability dimensions. Given the dimensions of sustainability, the total return and risk are decomposed into the three dimensions treated as the separate/independent outputs/inputs in separate constraints in (12).

$$\begin{aligned} & E_o^2 = \max_{z,\phi} \quad \phi \\ & \text{s.t.} \quad \sum_{j=1}^{n} z_j \sigma_{rj} \leq \sigma_{ro} \qquad r = 1,\ldots,s \\ & \qquad \sum_{j=1}^{n} z_j E(r_{rj}) \geq E(r_{ro})\phi \quad r = 1,\ldots,s \\ & \qquad z_j \geq 0, j = 1,2,\ldots,n \end{aligned} \tag{12}$$

The model in (12) will, therefore, have three risk constraints and three expected return constraints representing the risk and returns for the three sustainability dimensions. In such a model, the technology return and risk may be defined as a weighted average in the portfolio analysis. This model is preferred to that presented in (11) since it allows preference to be examined on each dimension independently. However, the model allows the technology to choose the sustainability dimension for which more emphasis will be placed in terms of the weighting. This is since the weights are local and differ between technologies.

3.3.2.3. Multiplicative modelling of sustainability dimensions (Model 3). To handle this preference problem between the expected returns across sustainability dimensions, it may be more appropriate to interact the various dimensions under study since the idea of sustainability fundamentally requires interaction between the dimensions. Here, only the joint probability distribution is explored. Yang et al. [55] have shown that the DEA approach can be extended using the multi-attribute utility theory with variable weights to include interaction terms to reflect value judgements. To cater for the need for interactions between the dimensions, therefore, the three return estimates are included as an interaction term as formulated in (13). This will require an estimation of a new risk variable defined as a product of the returns. This new risk variable for each technology is incorporated in (13) as $\widehat{\sigma}_j$. Also, note that the expected return and risk are estimated as in (6) and (7) respectively.

$$\begin{aligned} & E_o^3 = \max_{z,\phi} \quad \phi \\ & \text{s.t.} \quad \sum_{j=1}^{n} z_j \widehat{\sigma}_j \leq \widehat{\sigma}_o \\ & \qquad \sum_{j=1}^{n} z_j E\left(\prod_{r=1}^{s} r_{rj}\right) \geq E\left(\prod_{r=1}^{s} r_{ro}\right)\phi \\ & \qquad z_j \geq 0, j = 1,2,\ldots,n \end{aligned} \tag{13}$$

The rankings generated from (13) is most consistent with the principles of sustainability and will ensure that economic, social and environmental considerations are equally prioritised in the composition of different technologies.

3.3.2.4. Pairwise interactions between sustainability dimensions (Model 4). The potential problem with (13) is the impact a zero score on any dimension can have on the final ranking. A zero value on any dimension may mean no performance assessment based on the other dimensions can be undertaken. A renewable technology may have no environmental cost, for example, if only direct emissions are considered. In such circumstances, it is possible to conduct pairwise interaction as a compromise solution.

$$
\begin{aligned}
E_o^4 = & \max_{z,\phi} \quad \phi \\
\text{s.t.} \quad & \sum\nolimits_{j=1}^{n} z_j \widetilde{\sigma}_{rtj} \leq \widetilde{\sigma}_{rto}, r = 1, \dots, h-1, t = h+1, \dots, s \\
& \sum\nolimits_{j=1}^{n} z_j E\left(r_{rj} \cdot r_{tj}\right) \geq E\left(r_{ro} \cdot r_{to}\right)\phi, r = 1, \dots, h-1, t = h+1, \dots, s \\
& z_j \geq 0, j = 1, 2, \dots, n
\end{aligned} \tag{14}
$$

Note that $\widetilde{\sigma}_{rtj}$ in (14) represents the standard deviations of the expected return for sustainability dimensions r and t estimated using pairwise interaction. The variance is estimated like (7) except that r is 2 in each case. The model presented in (14) retains the interactions between the dimensions as required by sustainability while catering for the possibility of zero scores on a dimension. In essence, this approach examines the other outcomes in the triple bottom line framework such as technologies that are not environmentally damaging and support society but come at high cost (socio-environmental), economically viable technologies which support society but have high environmental implications (socio-economic) and those that are economically profitable, do not burden the environment but do not provide sufficient support for society (eco-efficiency) [46]. The overall technology expected return and risk under such evaluation is the average of the pairwise interactions.

3.3.2.5. Multilinear assessment of sustainability dimensions (Model 5). An alternative compromise solution that addresses the problem of zero data on the dimensions and which also captures the joint effects across dimensions is presented in (15). This approach captures both the marginal effects and the joint effects between the dimensions.

$$
\begin{aligned}
E_o^5 = & \max_{z,\phi} \quad \phi \\
\text{s.t.} \quad & \sum\nolimits_{j=1}^{n} z_j \left(\sum\nolimits_{r=1}^{s} \sigma_{rj} + \widehat{\sigma}_j \right) \leq \left(\sum\nolimits_{r=1}^{s} \sigma_{ro} + \widehat{\sigma}_o \right), r = 1, \dots, s \\
& \sum\nolimits_{j=1}^{n} z_j E\left(\sum\nolimits_{r=1}^{s} r_{rj} + \prod\nolimits_{r=1}^{s} r_{rj} \right) \geq E\left(\sum\nolimits_{r=1}^{s} r_{ro} + \prod\nolimits_{r=1}^{s} r_{ro} \right)\phi \\
& z_j \geq 0, j = 1, 2, \dots, n
\end{aligned} \tag{15}
$$

4. Empirical assessment

To allow for a comparison of our results to the approach in the literature, the data by Arnesano et al. [3] on portfolio optimisation of the Italian electricity generation mix is used. In their assessment, generation cost comprised environmental (CO_2 cost), societal (external costs) and economic (industrial) dimensions. As such, we can model all three dimensions of sustainability in our assessment. In their study, the relationship between these dimensions was modelled as a sum where the inverse of the sum of generation costs, comprising industrial, external, and direct and indirect CO_2 costs, was maximised given the risk associated with each generation technology.

4.1. DEA evaluation of sustainability dimensions

Arnesano et al. [3] examined the Italian context to verify whether a different energy mix could be identified that minimises financial costs and risks, while at the same time examining environmental sustainability. The environmental dimension, represented by CO_2 costs, was based on a lifecycle estimate of the environmental emissions of the technology, as such, even renewable energy sources like hydro, wind and solar PVs incur some environmental cost in the production due to embodied emissions. Assessment based on the lifecycle perspective does not limit the environmental impact to only the generation of the resources, but the environmental impacts from the 'cradle-to-grave' lifecycle thinking perspective. The composition of total cost included an external cost dimension, which represents all other costs due to the production of energy that is not sustained by the power plants themselves but by society. This external cost is used as the social dimension of sustainability in this chapter. A summary of the data from the paper for the 10 technologies comprising both renewable and non-renewable sources are presented in Table 1.

From the values in Table 1, it is expected that renewable energy generation sources (hydro, solar [PV], wind and biomass) will outperform their non-renewable counterparts (gas and coal) if the technologies are considered along with environmental and social perspectives of sustainability. This is because renewable sources generally have relatively lower environmental and societal costs and have relatively lower risk levels compared to most non-renewable technologies. Non-renewable sources like coal and gas have a comparative advantage in terms of the economic (industrial) dimension. Nuclear energy is also expected to be a higher performer since it is also associated with lower costs, though the risk may be high. When cost is examined at the total level, it is seen that the high industrial costs associated with renewables erode the gains it makes on the other cost dimensions. The industrial cost of PV, for example, represents 98.9% of its total cost of generation. At the national level, sustainable generation mix planning implies an optimal mix that effectively caters for environmental and social objectives together with economic implications. In this section, therefore, the effect of the structure of the cost/return on the rankings of the various technologies and its implications on the portfolio generated are examined.

Table 2, shows the risk-adjusted performance scores and rankings of the technologies estimated by Model 1 [Eq. (11)] where the costs are combined as a sum of the dimensions. As expected, due to the use of the additive composite score, poor performance on some sustainability dimensions is compensated by higher performance on the others. For example, PV is disadvantaged in terms of comparative performance due to high industrial (economic) costs, although it has a low environmental and social impact as well as risk. Additionally, gas (100–160) and gas (660) which are fossil fuel-based technologies are among the higher performers although they are among the riskiest technologies in terms of environmental impact.

Next, the total return is decomposed. The three dimensions are treated as separate outputs and inputs in separate constraints as in Model 2 [eq. (12)] with the results presented in Table 3. Arnesano et al. [3] do not provide estimates for the risk of the social (external) dimension due to the unavailability of historical data. As such, we also do not include any risk score (and constraint) for the social dimension.

From Table 3, the preference evaluation of the technologies is deemed relatively more consistent with sustainability than previously shown in Table 2 since dimensions are independently compared based on Pareto preference. However, in forming an overall score, since each dimension is compared across technologies, the model will be less discriminatory than the previous model. Additionally, technologies choose which dimension more emphasis is placed on in their weighting. That explains why gas (660) is among the better performers since it places more emphasis on its higher economic performance. Coal (320) also places more weight on its low industrial costs (high economic returns), though it has relatively poor performance on the environmental and societal dimensions. This, however, does not conform with the traditional idea of sustainability since emphasis can be placed on one dimension to the neglect of other ones.

The next table explores how interacting the expected returns for the sustainability dimensions affect the scores and rankings. These

Table 1
Cost and risk estimates.

Technology	CO_2 Cost (Environmental)	External Cost (Societal)	Industrial (Economic)	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)[a]	0.172	0.340	5.457	5.968	8.19
Hydro (<10)[a]	0.172	0.340	6.410	6.922	27.46
Wind (>0.1–2)[a]	0.041	0.150	13.293	13.484	3.75
PV (0.5–1)[a]	0.272	0.160	39.746	40.178	4.02
Biomass (<15)[a]	0.234	2.650	13.223	16.107	12.57
Nuclear (1100)	0.021	0.250	5.082	5.353	16.72

[a] Renewable energy source.

Table 2
Additive modelling of sustainability dimensions (Model 1).

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

Italicized values do not conform with our *a priori* expectations of technology ranking based on the ideals of sustainability.

interactions align more with the idea of sustainability than the additive model. Due to the relatively higher risk scores on the economic dimension (see Table 3), the economic return variable is transformed and replaced with the square root of the returns in Table 3, for each technology. Risks are estimated, with respect to eq. (7).

Results, presented in Table 4, conform much better to our *a priori* expectations of the rankings, with most renewables and nuclear among higher performers and fossil-based fuels among the lower performers. Among the top performers are wind, nuclear, hydro and PV. This interaction between the dimensions allows for better incorporation of all three dimensions of sustainability in the portfolio generation. However, it must be noted that zero value on any dimension will mean no performance score for that technology. Technology may have no environmental cost, for example, if only direct emissions are considered and not the whole lifecycle emissions which would account for embodied emissions.

To cater for the implication of a zero score on a dimension on the final score for such special occasions, it is reasonable to use compromise solutions. Ranks generally stay similar to those presented in Table 4 while catering for the possibility of zero scores on a dimension. Table 5 shows the rankings using the two compromise solutions that incorporate some level of interaction between the dimensions. For both compromise solutions, renewables outperform non-renewable sources, which is consistent with our *a priori* expectations.

While pairwise interaction captures the joint effect between two dimensions at a time, the multilinear form captures both the joint effect of the three dimensions and their marginal effects. Therefore, for pairwise interaction, if there is a value of zero on any one dimension, the expected return will comprise only the interaction of the two remaining

Table 4
Multiplicative modelling of sustainability dimensions (Model 3).

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	0.7491	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

Table 5
Compromise solutions (Models 4 and 5).

Technology	Pairwise Interaction		Multilinear	
	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

Table 3
Separating the sustainability dimensions (Model 2).

Technology	Return Env.	Return Soc.	Return Eco.	Risk Env.	Risk Eco.	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

Italicized values do not conform with our *a priori* expectations of technology ranking based on the ideals of sustainability.

dimensions. Consequently, such a technology will not dominate another technology with non-zero values. In the multilinear model, the expected return of technology comprises both the additive and multiplicative terms. Hence, if technology has zero value on any dimension, its expected return will be lower since it will be made up of only the additive component.

We used the Simar and Wilson [41,42] bootstrapping technique to estimate the bias-corrected scores for all previous risk-adjusted performance scores. This is because DEA scores can be influenced by outlying observations and statistical noise. Additionally, we present the 95% confidence intervals for the bias-corrected scores. The rankings of the sources from the bias-corrected scores are consistent with the original estimates presented in the previous tables. This shows that our results are not subject to the risk of outlying observations or statistical noise. The bootstrapping scores are reported in the supplementary materials.

We show in Table 6 a comparison of the various models discussed. We present a heatmap of the rankings among the technologies for each model and the correlation coefficient between the models. Evidently, the significantly strong correlations between model 3, model 4 and model 5 show that both the interactions and the comprise solutions underscore the reliability of interaction as an aggregation method in reflecting all dimensions in the ranking. The low and insignificant correlation between the additive model and the interacting models also shows the validity of the interacting models to reflect the sustainability outcome based on all the dimensions considered.

4.2. Constructing optimal generation portfolios

We have showed that the aggregation approach for generating the total cost/return used for portfolio optimisation can impact preference between technologies and their rankings. The next question is whether changes in the aggregate the cost/return affect the optimal portfolio of technologies generated using the Markowitz approach. Two portfolios, the maximum return and minimum risk portfolios are constructed for each of the cost configurations examined in this section. For the maximum return portfolio, the expected return of the portfolio of technologies is maximised given risk and capacity constraints. Minimum risk portfolio constructs the optimal portfolio that minimises the overall portfolio risk. The minimum risk portfolio is usually the most diversified portfolio while the maximum return portfolio is the least diversified. For the Italian case, the minimum and maximum capacity constraints showing the lower and upper bounds for the different technologies considered are given in the supplementary materials.

In Fig. 1, the optimal portfolios of technologies excluding nuclear energy are presented. The current generation mix of Italy, for the period under study, had no nuclear generation input, as such the portfolios presented in Fig. 1 exclude the nuclear option. CO_2 emissions have been estimated based on the allocation of gas and coal options using the emission factors of 55.82 kg/GJ and 94.073 kg/GJ respectively, for the annual electricity demand of 314.57 TWh consistent with Arnesano et al. [3]. Full portfolio characteristics are presented in the supplementary materials.

Maximum return portfolios for the additive (model 1) and multiplicative (model 3) options show a clear difference. The optimal portfolio based on an addition of the sustainability dimensions has only 30% total allocation to renewable energy sources, although maximum capacity constraints allow for at most 61% allocation to renewable sources. Even PV gets no allocation in the generation mix. The portfolio is, therefore, dominated by non-renewable sources with gas (660) receiving the highest allocation of about 48%. Compare that to the portfolio generated based on the interaction of the components (model 3) of the total return for the technologies. Here, 61% of the portfolio allocation has been given to renewable generation sources, thereby, ensuring a massive reduction in the CO_2 emissions based on the additive model (model 1). This is a cleaner generation mix compared to the additive portfolio which allows for more non-renewable sources due to lower economic cost alone.

For the minimum risk portfolio, it is seen that the additive model slightly outperforms the multiplicative model, probably because no risk for the social dimension was captured in the original data, although the expected returns reflect the social dimension of sustainability. Note that discussions in the previous section were based on the maximisation of return and its implication on risk, however, the portfolio generated by the multiplicative model for the minimum risk portfolio does not seem

Table 6
Relationships between the aggregation methods.

Technology	Model 1	Model 2	Model 3	Model 4	Model 5
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
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

$p < 0.05$ *, $p < 0.01$ **, $p < 0.001$***.
Spearman's correlation coefficients are reported.

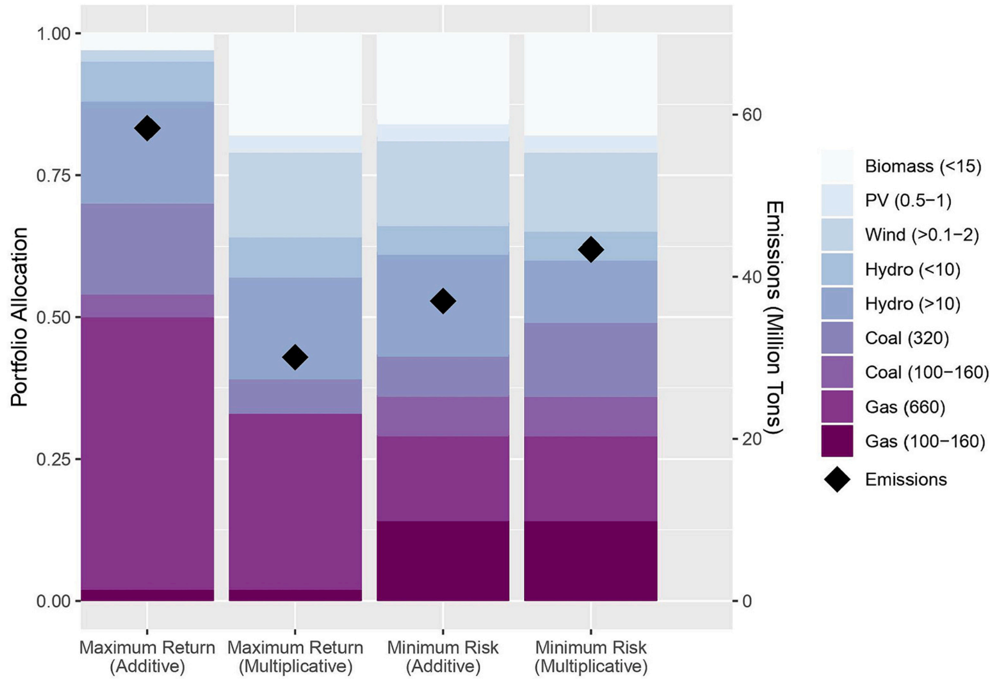

Fig. 1. Optimal electricity production mixes and CO_2 emissions without the nuclear option. The diagram shows both the maximum return and the minimum risk portfolios for the additive and multiplicative aggregation of sustainability dimensions.

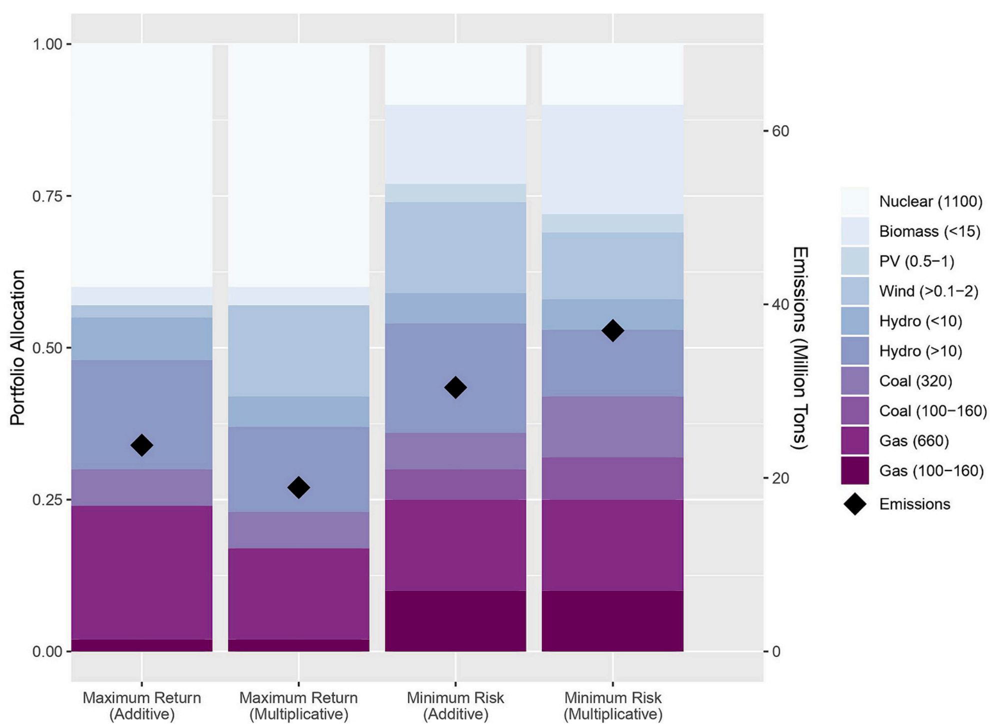

Fig. 2. Optimal electricity production mixes and CO_2 emissions with the nuclear option. The diagram shows both the maximum return and the minimum risk portfolios for the additive and multiplicative aggregation of sustainability dimensions.

very different from that generated by the additive model. Generally, the allocations for the minimum risk portfolios are identical with renewables comprising 56% of the additive model and 51% in the multiplicative model.

Fig. 2 shows the maximum return and minimum risk portfolios for the set of technologies including nuclear energy. Regardless, renewable content in the multiplicative model is higher than in the additive model. Observations made earlier for the minimum risk portfolio remains the same when nuclear energy is included in the optimal portfolio.

Finally, in the case of zero data on some dimensions, compromise solutions based on pairwise interaction and multilinear models are presented. The optimal portfolios using these approaches have been presented for no nuclear and nuclear cases in Fig. 3 and Fig. 4 respectively. In the figures, the optimal solutions are compared to the current

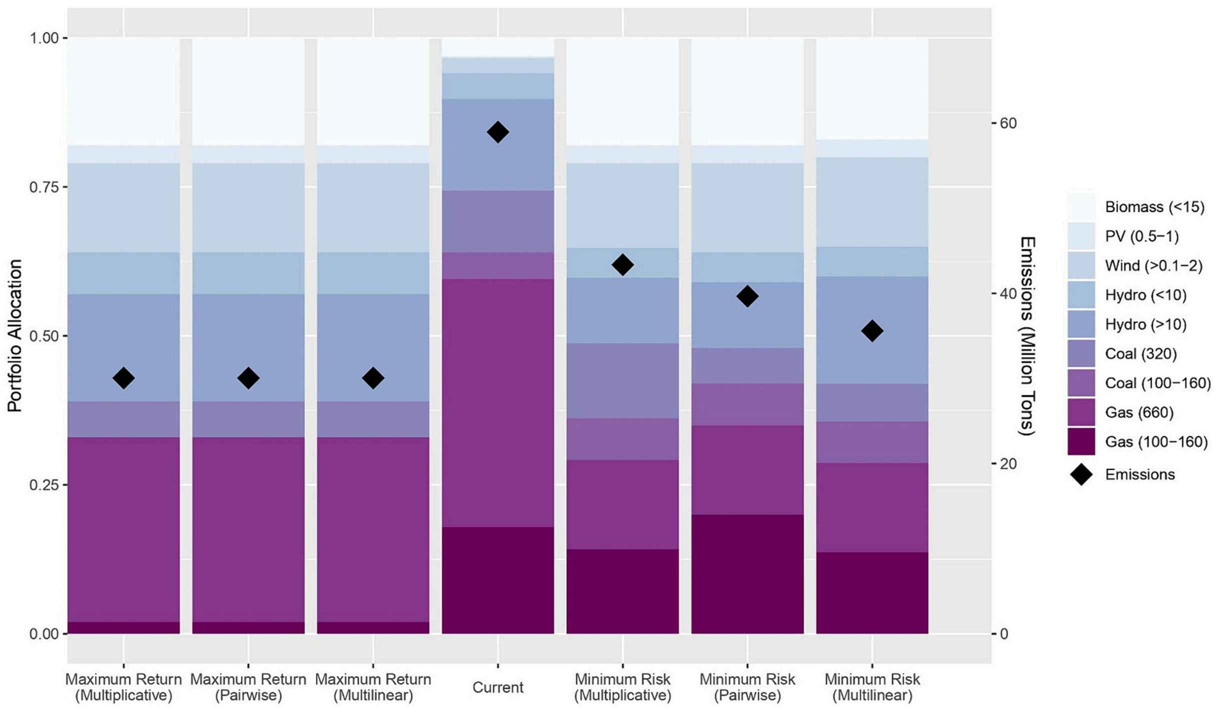

Fig. 3. Comparison of compromise solution with other solutions without the nuclear option.

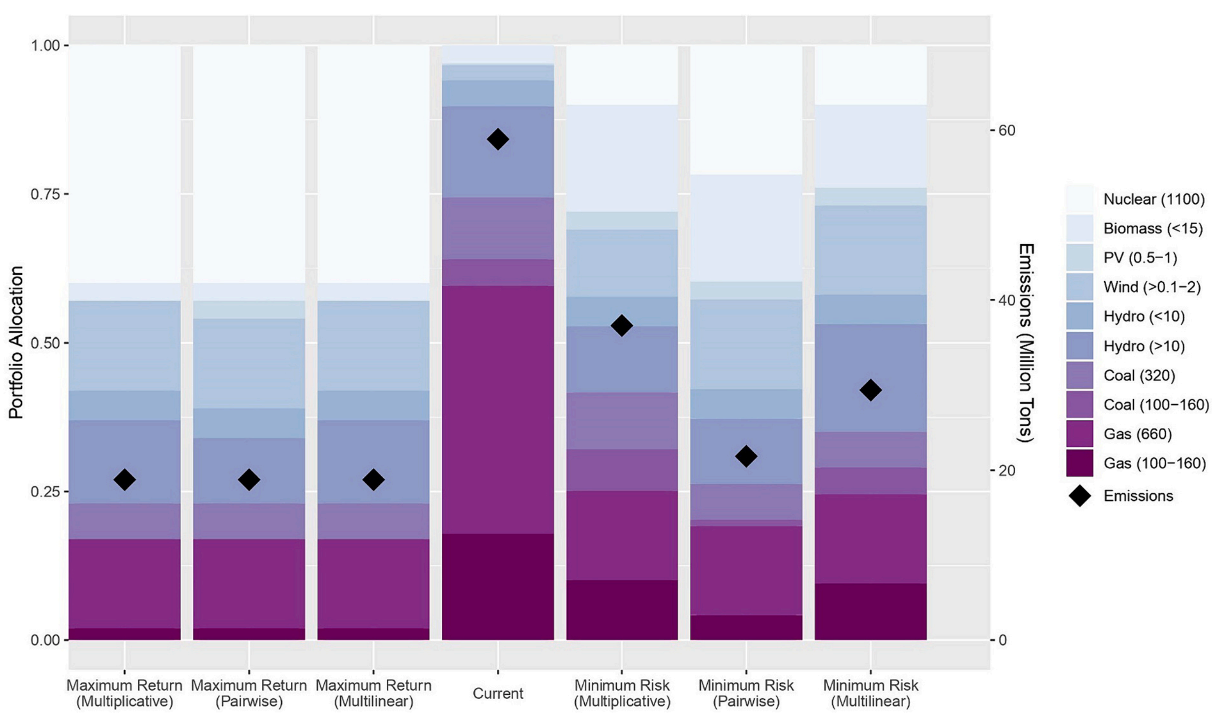

Fig. 4. Comparison of compromise solution with other solutions with the nuclear option.

Italian mix as well as the optimal solution in the multiplicative model. While the maximum return portfolios give similar emission levels, the compromise solutions outperform even the multiplicative model in the minimum risk case.

The existing portfolio (current) in the Italian case was characterised by high levels of carbon emissions and low levels of renewable energy sources in the mix. Only 26% of the electricity generation was from renewable sources. Any of the scenarios reported in Fig. 3 and Fig. 4 presents a portfolio with less emissions potential and higher levels of renewable energy sources. This is because the multiplicative aggregation approach and its compromise alternatives are better in giving importance to all the identified sustainability dimensions which are being modelled. It takes a more comprehensive account of the policy objectives into account rather than economic considerations. Considering compromise solutions for situations with zero scores on certain dimensions can be a practical approach. Energy policies could benefit from flexible models that take into account data limitations. This would ensure that decisions are still well-informed and reliable, even when complete information is not available. In essence, the research findings directly contribute to the development of effective and forward-thinking energy mix planning policies. This helps policymakers navigate the complexities of sustainability and optimise the use of diverse energy sources for a more resilient and environmentally friendly energy landscape.

4.3. Discussion and implications for policy

Energy policy should prioritise the need for secure, affordable and clean energy system [54]. This requires the expansion of energy infrastructure to those with access and ensuring that the energy supplies are reliably available. Countries must prioritise investing in clean energy sources such as solar, wind, and thermal energy, while ensuring universal access to affordable electricity [49]. Sustainability should be at the forefront of long-term energy-mix planning decisions, where economic costs should not be the main consideration. Instead, the impact of various generation sources on the environment and society should be given equal importance.

Researchers and practitioners have been working towards developing a sustainable mix of generation sources that considers the need for energy security and climate change mitigation objectives. They have modelled the different dimensions of sustainability in their assessments. Previous studies have suggested that a sustainable generation mix could be achieved by adding social and environmental cost estimates to the levelized cost of energy [24]. However, this traditional approach to constructing a sustainable generation mix may not effectively consider all dimensions of sustainability. More emphasis is placed on the economic dimension than the social and environmental dimensions of sustainability.

We agree with deLlano-Paz et al. [13] that greater flexibility is required in the modelling to increase the share of renewable technologies in the generation mix. The aggregation method selected is vital to ensuring equitable consideration of all sustainability dimensions in the optimal portfolio. Additive aggregation of the cost components can allow poor performance on some dimensions to be compensated by good performance on others [27]. Moreover, there is a large difference in the size of the estimates used for the various dimensions, which means that additive aggregation may not effectively give renewable generation sources an equal opportunity of being selected as non-renewable sources.

Our investigation shows that various multiplicative aggregation options better conform to our expectations of technology rankings than additive aggregation. When these aggregate cost/returns and risks are subjected to portfolio optimisation, a larger proportion of renewable energy sources are included in the optimal portfolios in the multiplicative aggregations compared to the additive ones. Compared to Arnesano et al. [3] optimal portfolios, which had on average 43% (SD = 0.1870) renewable energy inclusion, multiplicative aggregation techniques in the study achieved an average of 57% (SD = 0.0462) renewable energy inclusion in the portfolio without even considering nuclear energy.

The research underscores the need for a balanced and integrated approach to energy planning that equally considers the relevance of environmental, social, and economic dimensions. Policies that recognise the interdependence of these dimensions can lead to more secure and sustainable energy systems. It is crucial for policymakers to consider all dimensions of sustainability when deciding on incentives, subsidies, or regulations. They must ensure that all dimensions are adequately represented in the aggregated value, which is the basis of the policy decision. This paper advocates for models that capture interactions between sustainability dimensions, presenting a more nuanced understanding of technology performance. Energy policies that embrace such models can better align with sustainability goals and achieve more favourable outcomes in terms of environmental impact, societal benefits, and economic feasibility. Flexible models that account for data limitations are necessary to ensure that decisions are still informed and reliable even when complete information is not available.

5. Conclusion

This paper examines the implication of adding environmental and social costs to the total generation cost used for sustainable portfolio optimisation models. We provide methodological insights into how to enhance the assessment of sustainable energy portfolio diversification in energy mix planning. The study highlights the limitations of current methods and provides alternative approaches for incorporating the triple bottom line sustainability dimensions into such assessments.

Traditional approaches to this energy mix planning problem have generally relied on the mean-variance approach and have incorporated social and environmental dimensions in the estimation of the expected returns of the technology. However, our investigation shows that the nature of the aggregation of these dimensions is critical in equally capturing the relevance of all the dimensions of sustainability. This study, therefore, promotes the sustainability assessment of energy generation systems by combining environmental and external cost components with industrial/economic costs through exploring interactions and other relationships between the various components.

We observe that the nature of the aggregation between the dimensions has an impact on the performance score and rankings of the energy generation sources. We also observe a large impact on the mix of sources in the optimal portfolio. If policymakers find environmental and social implications as equally important to economic factors in energy mix planning, then we find additive aggregation as ineffective since it has the potential to disadvantage renewable energy sources. It is, therefore, not surprising that deLlano-Paz et al. [13] observe that portfolio optimisation has a limitation when it comes to assessing the impact of the inclusion of renewable technologies in the portfolio. We find that multiplicative aggregation provides the opportunity to better model the effect of renewable sources in sustainable mix planning.

While our study reveals new insights for the use of modern portfolio theory in energy mix planning and policy, we limited our evaluation to the portfolio optimisation problems. However, the aggregation problem may be evident in other methods for energy mix-planning such as stochastic programming and optimisation and MCDM techniques. While we have observed attempts in the MCDM literature to address this issue, we have observed little consideration in the optimisation literature. This calls for further research into the effect of various aggregation methods on the optimal mix using other optimisation approaches. In the empirical assessment, data for the Italian case used previously in the literature was adopted. The choice of this data was informed by the existence of cost data on the three sustainability dimensions and the ability to compare the findings with existing literature. Reliance on existing research data resulted in some challenges with the determination of risks. The social (external) dimension, for example, did not have a risk in the original application. Further research could generate cost and risk data from historic data series. While the focus was on the composition of costs, similar arguments could be made about the composition of risk, especially when it is considered that risk for an energy technology does not only come from fuel cost but it is an amalgamation of different dimensions, including CO_2 cost volatilities. Finally, we hope that based on our findings, future research on sustainable energy mix planning using portfolio optimisation will move away from additive aggregation as the method for determining the technology risks and returns.

CRediT authorship contribution statement

Charles Turkson: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Wenbin Liu:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization. **Adolf Acquaye:** Writing – review & editing, Validation, Supervision, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2024.123017.

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