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Sustainability Indicators Correlation Matrix

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Abstract: This study explores the complex interplay between economic growth, environmental preservation, and energy efficiency in the context of sustainable development. Leveraging analytical tools such as the OSeMOSYS model and Pearson correlation coefficient, the research investigates how economic decisions impact energy resource utilization and environmental quality. Key sustainability indicators, including Energy Payback Time (EPBT), Internal Rate of Return (ITR), and Climate Change Impact Mitigation (IMPcc), are analyzed within the framework of the Atlantis energy system. The study emphasizes the need to balance economic priorities with environmental considerations to achieve sustainability objectives effectively. Furthermore, the research evaluates the correlation between sustainability indicators when integrated into the optimization process of the OSeMOSYS energy modeling system. This approach, advocated in previous studies, underscores the importance of incorporating sustainability metrics into decision-making processes. In conclusion, the findings highlight the necessity of reevaluating the weighting of indicators within optimization functions to prioritize sustainability goals. By providing insights into the complex relationships between economic, energy, and environmental factors, the study contributes to advancing sustainable development practices for policymakers, businesses, and society as a whole.

Keywords: Correlation matrix, OSeMOSYS, Sustainability indicators, Pearson correlation coefficients.

I. INTRODUCTION

Sustainable development has emerged as a paramount global priority in recent decades, necessitating the harmonization of economic progress, environmental preservation, and energy efficiency, all while striving for social equity [1]. While these aspects may be tackled individually, their intricate interconnections underscore the interdependence of their impacts [2]. Economic decisions, for instance, wield considerable influence over both the environment and the energy landscape. Likewise, environmental degradation can cascade into economic ramifications and the availability of energy resources [3]. This study delves into these intricate dynamics, identifying pivotal correlations and their far-reaching implications. To gauge this interplay, it relies on analytical methodologies and statistical tools, notably leveraging the OSeMOSYS model alongside the Pearson correlation coefficient.

OSeMOSYS, an open-source energy optimization model [4], assumes a central role in this endeavor, particularly in its extended version, which integrates sustainability indicators as critical facets of the objective function. These indicators encompass metrics such as Energy Payback Time (EPBT) for assessing energy sustainability, Internal Rate of Return (ITR) for gauging economic sustainability, and Climate Change Impact Mitigation (IMPcc) as an indicator of environmental sustainability [5], [6]. Employing ATLANTIS as a case study, chosen for its extensive dataset, proves instrumental in comprehending how economic decisions shape both energy resource utilization and environmental quality.

Through the application of the Pearson correlation coefficient [7], this study scrutinizes linear relationships between pivotal variables, including in the breakdown of energy production, categorized into renewable energy, fossil fuels, and nuclear energy; the Economic costs encompass capital costs, fixed costs, and variable costs; and the Emissions output. The resultant insights offer a holistic understanding of how economic policies intricately influence energy and environmental sustainability. This holistic approach not only aids in identifying effective strategies to advance sustainable development but also underscores the imperative of balancing economic imperatives with environmental safeguards.

Moreover, the practical interpretation of the identified correlations furnishes comprehensive insights into the intricate interplay among these dimensions, offering valuable guidance for policymakers, businesses, and society at large in their pursuit of sustainable development.

II. METHODOLOGY

The purpose of this study is the evaluate the correlation between sustainability indicators when they are used as optimisation constraints in an energy modelling system using the OSeMOSYS code. Consideration has been given to the methodology advocated in [8], which emphasises the inclusion of sustainability indicators as an extra cost. The statistical correlation matrix is employed exclusively for this purpose. The Atlantis energy framework has been chosen as a case study to achieve the stated objectives.

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The focus of this section is to provide a concise overview of the integration of sustainability indicators into OSeMOSYS, as developed in [8]. It also covers the concept of the statistical correlation matrix and the evaluation procedures used to determine the degree of correlation between sustainability indicators.

A. *Sustainability indicators integration into OSeMOSYS*

In prior research [8], a methodology was developed to integrate sustainability indicators into the optimization function of the Open-Source Energy Modeling System (OSeMOSYS), aiming to bolster the software's sustainability capabilities. OSeMOSYS is a versatile open-source software package utilized for energy modeling and analysis, empowering policymakers, researchers, and energy experts to identify cost-effective energy mixes tailored to their specific requirements [4], [9].

To address this, sustainability indicators are incorporated into OSeMOSYS within the optimization function through a process akin to multi-objective optimization, delineated by correction factors linked to the various indicators. These indicators encompass energetic sustainability (EPBT), economic sustainability (ITR), environmental sustainability (IMPcc), and their convolution. Consequently, the optimization function transitions into a multi-objective framework, with each indicator serving as an additional cost factor. This introduction of supplementary costs enables the consideration of sustainability criteria during the optimization process, significantly influencing the overall optimization outcome, rather than being mere supplementary expenses. The extended optimization function, referred to as Sustainable Optimization Function (Sus_Op_index), is described in Equation 1.

$$\text{Sus\_Op\_index} = \sum_{y}\left(\text{Sus\_EPBT}_y + \text{FixCost}_y + \text{Sus\_ITR}_y + \text{Sus\_IMPcc}_y\right) \tag{1}$$

With:

$$\text{Sus\_EPBT}_y = \sum \text{VarCost}_{y,t}\left(1 + F_{\text{EPBT}_t}\right) \tag{2}$$

$$F_{\text{EPBT}_t} = \left(\frac{\text{EPBT}}{\text{ULT}}\right)_t \tag{3}$$

$$\text{Sus\_ITR}_y = \sum \text{CapCost}_{y,t}\left(1 + F_{\text{ITR}_t}\right) \tag{4}$$

$$F_{\text{ITR}_t} = \left(\frac{\text{ITR}}{\text{ULT}}\right)_t \tag{5}$$

$$\text{Sus\_IMPcc}_y = \text{EmissionPenalty}\sum_{t}\text{Emission}_{t,y} \times F_{\text{IMPcc}} \tag{6}$$

$$F_{\text{IMPcc}} = \frac{\text{EmissRate}_t}{\text{MeErsEmissRate}} \tag{7}$$

Where:
y: Indicates the year in the time frame.
t: Indicates the technology.
Op_Standard: Corresponds to the Global costs integrated along the time interval under study,
$CapCost_{y,t}$ [$/KW]: Capital investment cost of a technology, per unit of capacity.
$FixCost_{y,t}$ [$/KW]: Fixed cost, O&M, of a technology, per unit of capacity.
$VarCost_{y,t}$ [$/KWh]: Variable cost of a technology for a given mode of operation (cost of fuel), per unit of activity.
$EmissCost_y$ [$/year]: Emission Cost, is entirely related to the penalties imposed for pollution

In the equation, modulation weights, Wj, ranging from zero to one has been introduced. This factor serves various purposes within OSeMOSYS: it enables the activation or deactivation of the incorporated correction and, based on the user's or client's expectations/needs, it can adjust the importance placed on energy sustainability within the optimization process, allowing for more flexibility. In this manner, if we set the weights to zero, we recover the standard optimization function of OSeMOSYS (Op_Standard) [10], as expressed in Equation 8.

$$\text{Op\_Standard} = \sum_{y,t}\left(\text{CapCost}_{y,t} + \text{FixCost}_{y,t} + \text{VarCost}_{y,t}\right) + \text{EmissCost}_y \tag{8}$$

B. Definition of the framework application

ATLANTIS, a fictional nation blending characteristics from both developing and developed countries, serves as a testing ground for the energy model developed by [11]. Within the OSeMOSYS framework, ATLANTIS is not merely a conceptual entity but rather an established experimental framework. It functions as a benchmark environment considered optimal by both users and developers of OSeMOSYS for new implementations, thereby enhancing result reproducibility. The energy matrix of ATLANTIS is comprehensive, encompassing a diverse array of technologies, ensuring the generation of representative results. The technical and economic data used in ATLANTIS are sourced from reports by the International Renewable Energy Agency and the IEA-Energy Systems Analysis Program – Technology briefs (E01, E02, E03, E06, E10, and E11).

To maintain consistency with prior studies [8], [10], we utilize the same dataset for both costs and stability estimator values, with the exception of nuclear technology. In this context, our study advocates for adopting a pessimistic estimate for the Energy Payback Time (EPBT) and Internal Rate of Return (IRR) associated with cradle-to-cradle treatment of high-activity waste, estimated at approximately 80 and 75 years, respectively. Regarding the penalty imposed for CO2 emissions, we rely on emission costs calculated in [10], where $50 per ton of CO2 is deemed sufficient to facilitate decarbonization. To ensure reproducibility, Table 1 summarizes the dataset utilized.

Table 1. Main power generation technologies input characteristics parameters [10]

Technologies	Economic Costs			Useful Lifetime (Year)	Capacity Factor (CF)	Sustainability Estimators		
	Fixed Cost (M$/GW)	Capital Cost (M$/GW)	Variable Cost (M$/PJ)			EPBT (Year)	IRR (Year)	CO_2 emission activity ratio (Mt/PJ)
Natural Gas (NGSC)	44	2300	24.05	30	1	8.17	11.7	0.132
Diesel Generator (DSGC)	36	900	22.49	30	1	12.68	14.7	0.193
Integrated Gasification Coal (IGCC)	148	3700	11.58	30	1	12.93	30	0.268
Heavy oïl (HFSC)	50	2300	30.23	35	1	29.33	14.7	0.203
Large Hydro (Hydro Dam)	60	4000	1.39	35	0.45	7.2	84	0
Mini Hydro (Hydro_Min)	65	4500	1.39	50	0.4	3.63	35	0
Distributed Diesel (Diesel_Gen)	55	1070	22.48	40	1	12.68	14.8	0.193
Photovoltaic Utility Grid (PV_UTL)	0	2000	1.39	25	0.35 Day 0 Night	3	2	0,003
Wind	0	1845	2.69	25	0.25	10.32	10	0,006
NEW Combined Cycle Gas Turbine (NGCC)	44	1100	16.17	35	1	8.17	11.9	0.101
Nuclear	0	3000	6.12	50	1	80	75	0.004

C. Correlation Matrix Based on Constraints

In this study, we'll utilize the Pearson method [7], [12] to gauge the correlation among various variables pertaining to both the energy-economic and environmental facets of sustainable development. To achieve this, we'll construct correlation matrices illustrating the linear connections among all variables under consideration. These matrices will unveil patterns and connections between the energy-economic and environmental dimensions of sustainable development, offering a deeper insight into their interplay within the realm of sustainability.

However, in a multidimensional study like ours, where numerous variables are at play, the correlation matrix isn't a static, single entity [12]. Instead, it serves as a tool to evaluate the strength and direction of relationships among multiple variables concurrently, within a defined set of relevant constraints [12], [13], [14].

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In this context, we've identified different constraint sets, based on merit variables, which can be applied either individually or collectively during the analysis. By employing constraint sets, we can refine datasets to create subsets that adhere to specific conditions or criteria. These subsets can then be analyzed independently, allowing us to focus on particular aspects or relationships within the data.

In our study, we'll generate a correlation matrix for each subset, resulting in a distinct matrix for each set of constrains. In the present study, the set of constraints is derived from the output results of the simulations carried out with OSeMOSYS, which consists of energy production, economic costs, and output emissions.

The Energy production feature covers the energetic production set of different types of energy systems, subset into renewable energy, fossil fuels and nuclear energy. These quantities represent the output levels of different energy sources generated within the OSeMOSYS simulation. With respect of economic costs includes the OSeMOSYS cost component, which consists of capital costs, fixed costs, and variable costs. Economic costs provide insights into the financial implications associated with different scenarios simulated by OSeMOSYS. And the output emissions refer to the emissions generated by the energy-producing activities included in the OSeMOSYS simulation. Output emissions represent the environmental impact of different energy production pathways and are crucial for assessing the sustainability of energy systems.

Named as SI_CorrMtxSet, the correlation matrix for sustainability indicators is depicted in Equation 9, where correlation coefficients are linearly applied among the indicators.

$$\mathrm{SI\_CorrMtx}^{\mathrm{Set}} = \begin{bmatrix} \mathrm{Cc}^{\mathrm{Set}}_{\mathrm{EPBT\_EPBT}} & \mathrm{Cc}^{\mathrm{Set}}_{\mathrm{EPBT\_ITR}} & \mathrm{Cc}^{\mathrm{Set}}_{\mathrm{EPBT\_IMPcc}} \\ \mathrm{Cc}^{\mathrm{Set}}_{\mathrm{ITR\_EPBT}} & \mathrm{Cc}^{\mathrm{Set}}_{\mathrm{ITR\_ITR}} & \mathrm{Cc}^{\mathrm{Set}}_{\mathrm{ITR\_IMPcc}} \\ \mathrm{Cc}^{\mathrm{Set}}_{\mathrm{IMPcc\_EPBT}} & \mathrm{Cc}^{\mathrm{Set}}_{\mathrm{IMPcc\_ITR}} & \mathrm{Cc}^{\mathrm{Set}}_{\mathrm{IMPcc\_IMPcc}} \end{bmatrix} \tag{9}$$

Where:

Set: Represents the set of constrain defined. It indicates the output data variables that make up the dataset for analysis; in OSeMOSYS this can include costs, emissions, and energetic production among others.

$Cc^{Set}{}_{EPBT\_EPBT}$: *The correlation coefficient between the indicator EPBT and EPBT.*

$Cc^{Set}{}_{ITR\_ITR}$: *The correlation coefficient between the indicator ITR and ITR.*

$Cc^{Set}{}_{IMPcc\_IMPcc}$: *The correlation coefficient between the indicator IMPcc and IMPcc.*

$Cc^{Set}{}_{EPBT\_ITR}$: *The correlation coefficient between the indicator EPBT and ITR.*

$Cc^{Set}{}_{EPBT\_IMPcc}$: *The correlation coefficient between the indicator EPBT and IMPcc.*

$Cc^{Set}{}_{IMPcc\_ITR}$: *The correlation coefficient between the indicator IMPcc and ITR.*

Each cell within this matrix will denote the Pearson correlation coefficient (Cc) between two specific variables, delineating the magnitude and direction of their linear relationship. The Pearson coefficient is derived by dividing the covariance of the two variables by the product of their standard deviations. Renowned for its intuitive interpretation and capacity to capture linear associations between variables, a value of r nearing 1 signifies a robust positive correlation, while near -1 indicates a strong negative correlation. Conversely, a value approximating 0 implies an absence of correlation altogether [14]. Prior to computing the Pearson coefficients, data preprocessing is crucial for standardizing/normalizing units and potentially transforming variables to adhere to a normal distribution [15]. The correlation coefficient for a pair of sustainability indicators under defined constraints can be computed using Equation 10.

$$\mathrm{Cc}^{\mathrm{Set}}_{\mathrm{X\_Y}} = \frac{\mathrm{Nr}^{\mathrm{Set}}\sum(\mathrm{XY}) - (\sum \mathrm{X} \sum \mathrm{Y})}{\sqrt{\left(\mathrm{Nr}^{\mathrm{Set}}\sum \mathrm{X}^2 - (\sum \mathrm{X})^2\right)\left(\mathrm{Nr}^{\mathrm{Set}}\sum \mathrm{Y}^2 - (\sum \mathrm{Y})^2\right)}} \tag{10}$$

Where:

$Cc^{Set}{}_{X\_Y}$: *correlation coefficient between parameters X and Y*

Σxy: sum of the product of each pair of corresponding sets of constraints of the two variables

Σx: sum of the sets of constraints of the first parameter

Σy: sum of the sets of constraints of the second parameter

Nr^{Set}: *Number of sets of constraints defined before that are applied.*

III. RESULTS AND DISCUSSIONS

In the framework of the Atlantis energy scenario, sustainability indicator objective functions have been optimized to infer the output variable constraints crucial for computing the correlation coefficients. Three key optimization functions utilize single estimators as the main variable in constructing the appropriate matrix. These single optimization functions are as follows:

i) energetic sustainability indicator optimization (Op_EPBT).
ii) Economic sustainability indicator optimization (Op_ITR).
iii) Environmental sustainability indicator optimization (Op_IMPcc).

To further enhance the discussion of results, additional optimization functions as a convolution of each sustainability indicator pair are considered. These include:

i) Energetic and Economic indicators optimization (Op_EPBT_ITR).
ii) Economic and Environmental indicator optimization (Op_ITR_IMPcc).
iii) Environmental and Energetic sustainability indicators optimization (Op_IMPcc_EPBT).

For each optimization function, the considered output parameters in their global values integrated over the studied period are shown in Table 2.

Upon analysing each indicator separately, it is evident that EPBT and IMPcc exhibit a more aligned behaviour, making them well-suited for decarbonization However, the importance of environmental sustainability has surpassed that of the energy sustainability indicator. This is evidenced by the paired optimisation trend between them which leans towards a consensus trend in renewable energy, emphasising the significant importance of both indicators. Meanwhile, emissions, fossil fuel production and costs have continued their path towards environmental sustainability. Broadly the pattern of IMPcc and EPBT is in sharp contrast to that of ITR, which promotes counter-decarbonisation outcomes.

Based on the findings presented in Table 2, two types of analyses have been conducted: Initially, the study evaluates the diverse effects linked to the application of individual and collective sustainability estimators. Subsequently, the corresponding correlation coefficients are computed. The merit variables associated with energy transition have been considered in both instances.

Table 2. Global output of the considered observable for each sustainable optimisation function.

Optimization Function		Energy Production Sources (%)			Economic Costs			Emissions (Ton CO_2 /MWh)
		Renewable	Fossil	Nuclear	Variable (M$)	Capital (M$)	Fixed (M$)	
Single Optimization Function	Op_EPBT	77	23	0	1607.45	3530.02	1465.41	0.13
	Op_ITR	31	69	0	2859	1967.37	926.50	0.32
	Op_IMPcc	72	6	22	1379.41	4201	1108	0.03
Pairing Optimisation Function.	Op_EPBT_ITR	45	55	0	3319.79	2158.09	994.17	0.28
	Op_EPBT_IMPcc	81	6	13	1177.05	3761.00	1443.93	0.03
	Op_ITR_IMPcc	44	39	17	3122.61	2267.60	939.16	0.16

A. *Direct evaluation*

The comparison between a single and convoluted indicator has been calculated to assess constructive or non-constructive interactions between the effects of applying different indicators. This comparison has been evaluated for each merit variable.

Starting with both energetic and environmental sustainability indicators, Fig. 1 plots the distribution of energy production categories, variable and capital costs, and emissions of Op_EPBT and Op_IMPcc against the paired convolution (Op_EPBT_IMPcc). The paired convolution ensures a similar level of decarbonisation to the IMPcc, with an 80% boost compared to the EPBT, which is tied to restrictions on nuclear energy (13% reduction) in exchange for a 16% increase in fossil technologies, the use of which leads to an increase in variable costs of almost a third compared to the paired convolution (Op_EPBT_IMPcc).

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As far as IMPcc is concerned, the comparison also shows an increase in the variable cost because of the Nuclear fuel cost, but 12% less than the comparison between (Op_EPBT versus Op_EPBT_IMPcc), as IMPcc tends to mitigate more polluting technologies, being 30% more than EPBT. In terms of capital investment, Op_EPBT_IMPcc, which incorporates more renewable energy features, incurs an almost 10% higher capital cost compared to both EPBT and IMPcc single optimizations, which exhibit similar behaviour in terms of their renewable energy deployment and thus their corresponding capital costs.

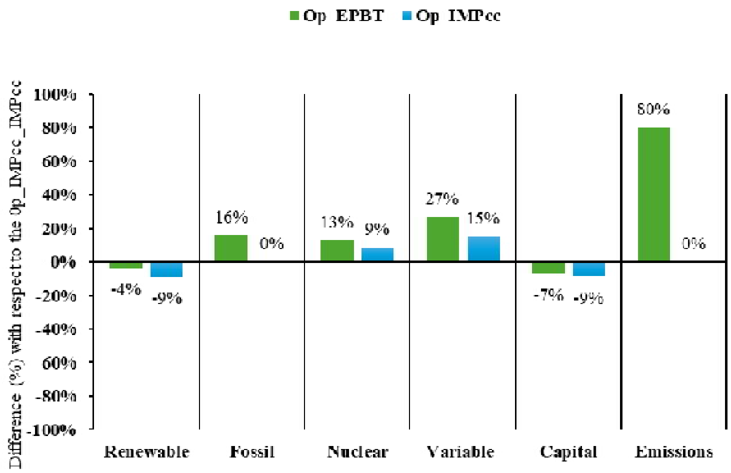

Fig 1. Share of the energy production categories, costs, and emissions of Op_EPBT and Op_IMPcc against Op_EPBT_IMPcc

The impacts of ITR don't seem to align with those of the other individually applied indicators across any of the merit variables. There is a bias towards ITR in both Op_EPBT_ITR and Op_IMPcc_ITR. For Op_EPBT_ITR, considering both indicators simultaneously results in a 30% increase in fossil fuel dependency and a burden on nuclear energy production. This is shown in Fig. 2, which illustrates the distribution of energy production categories, costs, and emissions for Op_EPBT and Op_ITR compared to Op_EPBT_ITR. As emissions follow the trend of ITR, Variable costs also correspondingly increase.

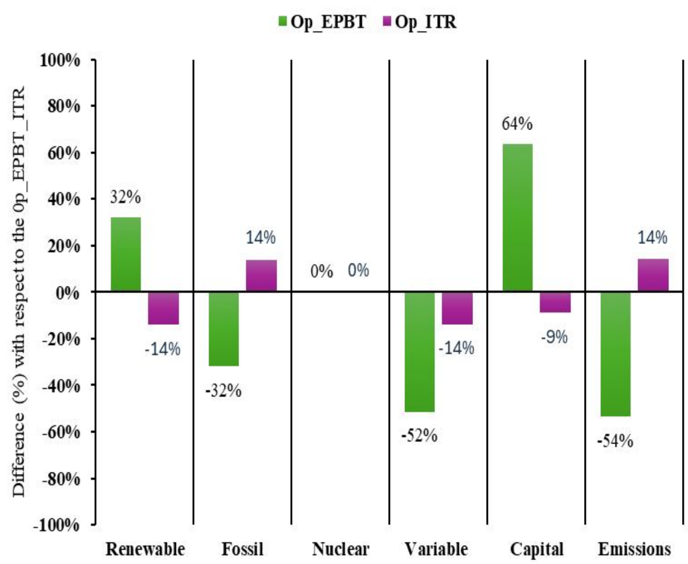

Fig 2. Share of the energy production categories, costs, and emissions of Op_EPBT and Op_ITR against Op_EPBT_ITR

Op_ITR_IMPcc, as opposed to Op_IMPcc, reduces renewable energy production by 30% and tends to encourage the growth of polluting technologies by at least 30%, thereby resulting in 40% more emissions. In all relevant trends, the paired analysis places economic sustainability ahead of environmental sustainability. This is evidenced in Fig. 3, depicting the allocation of energy production categories, costs, and emissions for Op_ITR and Op_IMPcc in comparison to Op_ITR_IMPcc.

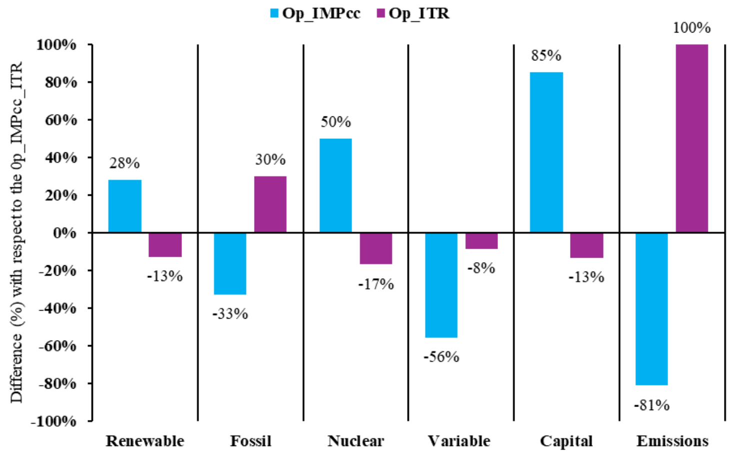

Fig. 3 Share of the energy production categories, costs, and emissions of Op_ITR and Op_IMPcc against Op_ITR_IMPcc

B. Correlation matrix coefficients associated with selected constraint sets.

A more detailed evaluation will be performed based on the results obtained using the correlation matrix approach. Various sets of constraints have been considered, including: i) Eps (categorised energy production sources, which comprise renewable, fossil, and nuclear), ii) EC (economic cost, which encompasses capital investment, fixed and variable costs), and iii) Em (emissions).

In the assessment of the level of correlation between the sustainability indicators, it has been found that the response is different depending on the merit variables being considered. To improve clarity, an analytical evaluation is proposed by constructing correlation matrices, where the variables under study define the set of constraints.

For a primary analysis, Equation 11 represents the correlation matrix, where the set of constraints applied includes EC (capital cost, variable cost, fixed cost), EP (renewable energy, fossil energy, nuclear energy) and EM (emissions). It's noteworthy that there is no correlation between economic and energy sustainability criteria, while environmental sustainability demonstrates a clear negative correlation with economic sustainability. However, energy and environmental sustainability display a correlation exceeding 80%.

$$\mathrm{SI\_CorrMtx}^{\mathrm{EP\&\ EC\&\ EM}} = \begin{bmatrix} 1 & 0.05 & 0.82 \\ 0.05 & 1 & -0.42 \\ 0.82 & -0.42 & 1 \end{bmatrix} \tag{11}$$

The mutual dependencies between the set of constraints significantly impact the level of correlation among the sustainability criteria. As a first remark, there is a fivefold interrelation between the variables set, including renewable and fossil fuel production, emissions, variable costs, and investment costs. For instance, CO_2 emissions are not only tied to the share of renewable energy sources or fossil fuels in the energy path but also to the investment in terms of capital costs. The fact is that the Op_IMPcc trend displays a lesser CO_2 emission including a significant proportion of renewable sources, thus making a higher investment cost. Whereas Op_ITR is seeking a quick investment payback time, renewable energy is often penalised in favour of fossil fuels, which do not require significant capital investment but are extremely polluting.

In summary, not all constraints can be fulfilled simultaneously. Additionally, there appears to be interdependence among the various options. To delve deeper into this matter, we'll evaluate correlation matrices with a more straightforward set selection.

1) *Correlations matrix coefficients associated with energetic production constraint set*: From the perspective of energy production, a clear directional relationship between sustainability indicators is noticeable, whether correlated or not (see Table 3). This can be further underscored by examining the correlation matrix, where the set of constraints utilized consists of the three defined energy production categories: renewable energy, fossil energy, and nuclear energy. Equation 12 shows the obtained results.

$$\mathrm{SI\_CorrMtx}^{\mathrm{EP}} = \begin{bmatrix} 1 & 0.23 & 0.86 \\ 0.23 & 1 & -0.29 \\ 0.86 & -0.29 & 1 \end{bmatrix} \tag{12}$$

A robust correlation of at least 86% between energetic and environmental sustainability indicators is observed. This correlation stems from both indicators promoting the extensive adoption of renewable energy production.

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Despite their intermittent nature due to a low-capacity factor, renewable technologies stand out from fossil fuel technologies thanks to their swift energy payback on a cradle-to-cradle basis. Renewable energy sources are cost-effective as they are free, unlike fossil fuel and nuclear technologies, which have variable fuel costs that make them less competitive.

However, the correlation between ITR and EPBT is weak at 23%. This weak correlation can be attributed to their differing approaches to energy production, except for fossil fuel category production. Moreover, in both cases, there is very little reliance on nuclear energy compared to fossil fuels and renewables, making them similar in that regard. Op_ITR relies more heavily on fossil fuels compared to Op_EPBT, which uses fossil fuels as a 20% backup to compensate for renewable energy intermittency. Additionally, the minimal correlation can be linked to the availability of energy sources, where the indicators are highly interdependent. ITR is closely linked to technology efficiency, favouring quick returns on investment. This bias leads to prioritizing fossil-fuelled facilities over widespread renewable energy technologies.

Economic and environmental sustainability indicators are anticorrelated by 29%. This divergence can be explained by the significant differences in renewable and fossil production between these indicators. Op_IMPcc limits polluting technology alternatives to a mere 6% of the energy mix, while the higher incorporation of renewable energy increases capital investment costs. This contrasts with Op_ITR, where half of the generation is from fossil fuels, favouring quicker economic returns.

2) *Correlation matrix associated with energy production and emission constraint sets:* Another aspect under evaluation is the impact of the proportion of polluting technologies included in the energy mix on emission levels. Fig. 4 illustrates the emission trends for each optimization function based on sustainability criteria and the distribution of energy generation categories. Specifically, Op_IMPcc demonstrates the lowest emission level per unit of production. In contrast, Op_ITR stands out as the highest polluter, emitting 90% more CO_2 than Op_IMPcc. Similarly, Op_EPBT emits 75% more emissions than Op_IMPcc.

The inclusion of emissions in the set of constraints alongside energy production categories significantly impacts the correlation matrix $SI\_CorrMtx^{EP\&EM}$, as demonstrated in Equation 13. Notably, the correlation coefficient associated with ITR undergoes a fundamental change. This alteration arises from each trend aligning with the triangular interrelation between emissions performance and the dependency on fossil fuels and renewable energy sources.

$$SI\_CorrMtx^{EP\&EM} = \begin{bmatrix} 1 & -0.01 & 0.74 \\ -0.01 & 1 & -0.67 \\ 0.74 & -0.67 & 1 \end{bmatrix} \tag{13}$$

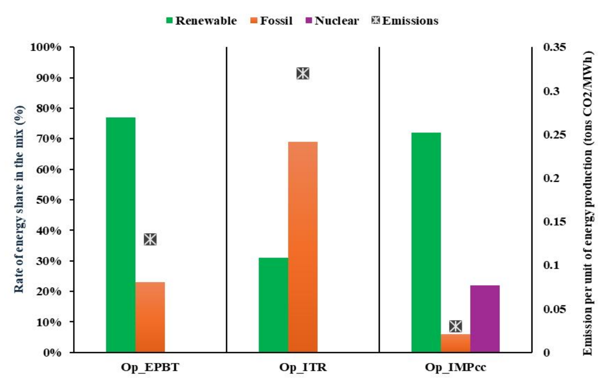

Figure 4. Emission trend by share of energy production categories for each optimisation function

EPBT and IMPcc exhibit a strong correlation, propelled by their joint emphasis on promoting renewable energy production (refer to Fig. 4 for further details). Moreover, their respective emissions trends align with the triangular interrelation among emissions, renewable energies, and fossil fuels. Despite noticeable disparities in emissions rankings, this triangular relationship yields a positive yet weak correlation between the economic indicator and the energy ones. It's crucial to note that Op_EPBT's reliance on fossil fuels in its energy mix contributes to its elevated pollution levels. Consequently, the correlation coefficient increases to 12%. Regarding the anticorrelation between the economic and environmental indicators, it stands as the highest calculated thus far (0.73). The rationale is clear: the most polluting energy sources tend to have the shortest economic return times.

3) *Correlations matrix coefficients associated with the economic constraint set:* The main cost component, encompassing variable, capital, and fixed costs, has been evaluated and presented in Table 3. Fig. 5 shows the cost trends for each of the optimisation sustainability indicators, highlighting the trend in cost components. Notably, the energy and environmental indicators exhibit the same cost trend, while the economic indicator demonstrates the opposite trend. Due to the significant penetration of renewable technologies, investment costs were approximately 44% higher for both Op_IMP_{CC} and Op_EPBT compared to Op_ITR. Conversely, as anticipated, Op_ITR incurs the highest fuel cost, being twice as expensive as Op_IMPCC and Op_EPBT.

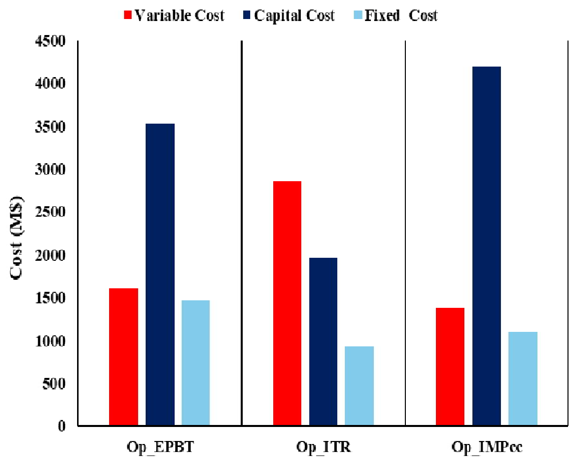

Fig.5 Costs components trend for each optimisation function

The correlation matrix, $SI\_CorrMtx^{EC}$, related to the cost component set, as shown in Equation 14, confirms the relationship among the indicators, as evident in Figure 5. As expected, there is a strong correlation between EPBT and IMPcc, with the correlation coefficient reaching its maximum value, signifying similar economic and energy trends. However, due to the contrasting trends exhibited by the ITR indicator, practically no correlated with both IMPcc, and EPBT.

$$SI\_CorrMtx^{EC} = \begin{bmatrix} 1 & 0.14 & 1 \\ 0.14 & 1 & 0.08 \\ 1 & 0.08 & 1 \end{bmatrix} \qquad (14)$$

C. Comparison and Decision table.

Based on the results obtained, Fig. 6 provides a visual representation of the Pearson coefficient values between sustainability indicators, categorized based on the variables utilized as constraints. This depiction allows for an insightful observation of the behavioural trends among the indicators. Notably, the strongest correlation emerges between EPBT and IMPcc, underscoring their closely aligned trajectories. Conversely, the association between ITR and EPBT reveals a weaker correlation, while the relationship between ITR and IMPcc demonstrates the strongest anticorrelation.

From the analysis presented in Fig. 6, significant insights emerge regarding the prioritization of sustainability indicators based on specific decision-making objectives. For instance, when the correlation coefficient between two sustainability indicators attains an absolute value (Cc = 1) for a particular set of decision objectives, it implies redundancy when these indicators are used in conjunction. In such scenarios, it is prudent to avoid their combined usage to prevent redundancy. This suggests that a single indicator can be sufficient to meet the corresponding decision goals effectively.

The observed redundancy between certain sustainability indicators, such as environmental and energetic sustainability, particularly in the context of economic cost constraints, underscores this point. When the correlation coefficient reaches unity, selecting either the energetic or environmental sustainability criterion alone is adequate to achieve the desired objectives. This approach ensures that decision-making remains efficient and avoids the unnecessary complexity and potential cost duplication associated with using multiple, redundant indicators.

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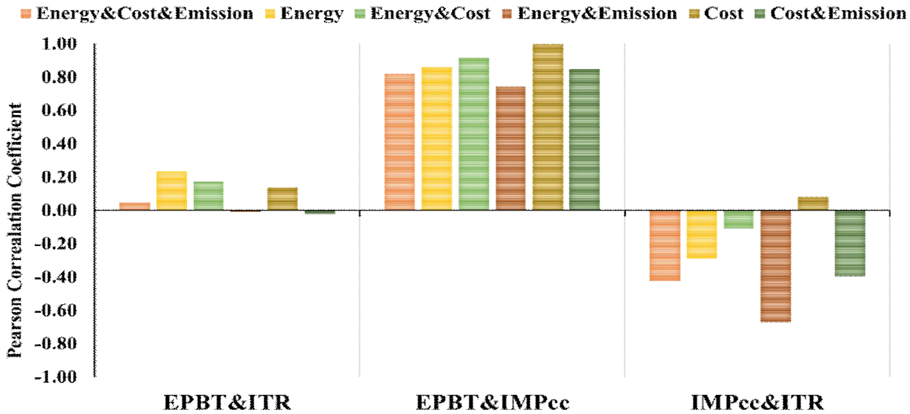

Fig. 6 Comparison of the person correlation coefficient for each set of constraint between the sustainability indicators

Still in the context of both energetic and environmental sustainability criteria, it is evident from Figure 3.7 that their correlation is not absolute across decision-making constraints, such as "energy production-emissions". Additionally, when addressing multiple objectives (e.g., cost, emissions, and energy production), both energetic and environmental sustainability indicators must be considered in tandem convolution. This necessity arises because no single criterion achieves perfect correlation with the others.

Focusing on economic sustainability criteria maintains its distinctiveness and relevance across various decision-making scenarios therefore it is crucial to pair it with either energetic or environmental sustainability indicators, regardless of the specific decision-making constraints. This approach ensures a comprehensive evaluation, as economic sustainability does not fully correlate with the other two criteria. In fact, economic sustainability criteria slightly positively correlate with energetic sustainability and negatively correlate with environmental sustainability (Figure 5). This nuanced interplay highlights the importance of a consideration of the economic sustainability-based decision making in convolution with at least another sustainability criteria to achieve well-rounded and effective decision-making.

Building upon these observed trends, Table 3.8 presents a decision table outlining the behaviour of each indicator concerning the considered output variables, which encompass energy production sources categorized according to economic costs (specifically, capital investment and variable costs) and emissions. These findings furnish valuable insights into the nuanced dynamics between sustainability indicators, thereby affording decision-makers the opportunity to tailor their prioritization based on specific objectives and requirements.

The obtained results provide the opportunity to adjust the importance of each sustainability criterion according to the objectives and needs of decision-makers. This can be achieved through modulation factors incorporated into the optimization function (denoted as Wj in Equation 1).

Table 3. Decision table detailing the behaviour of each indicator across various sets of constraints. (The upward arrows indicate a high influence of the indicators on achieving the proposed goals, whereas the downward arrows suggest the opposite. In the case of slanted arrows, the influence is not definitive and should be analysed in each specific case).

Optimization Function	Energy Production Sources			Economic Costs		Decarbonization
	Renewable	Fossil	Nuclear	Variable Cost	Capital Cost	
Op_EPBT	↑	↗	↓	↓	↑	↑
Op_IMPcc	↑	↓	↗	↓	↑	↑
Op_ITR	↓	↑	↗	↑	↓	↓
Op_EPBT_IMPcc	↑	↓	↓	↓	↑	↑
Op_EPBT_ITR	↗	↑	↓	↑	↓	↓
Op_ITR_IMPcc	↗	↑	↗	↑	↓	↓

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IV. CONCLUSIONS

In the current global paradigm, the significance of sustainability in the long-term energy transition cannot be overstated. Addressing challenges related to energy production and consumption, encompassing environmental, social, and economic impacts, is imperative. While multi-criteria Optimization modelling tools like OSeMOSYS provide valuable insights into energy systems, primarily focused on economic optimization, there's a growing consensus on the need to explicitly integrate sustainability considerations. Delving into sustainability indicators within OSeMOSYS reveals intricate interdependencies that significantly influence energy system planning and decision-making toward specific sustainability objectives. Among these indicators, Energy Payback Time (EPBT), Investment Payback Time (ITR), and Climate Change Mitigation Impacts (IMPcc) have been evaluated within the "cradle to cradle" philosophy.

The assessment of correlation matrices, employing the Pearson method, offers a quantitative analysis of these dependencies across various boundary conditions. Merit variables, such as energy production categorized into renewable, fossil fuels, and nuclear; economic costs including capital, fixed, and variable costs; and emissions, serve as constraints for calculating correlation coefficients. These constraints can be applied individually or collectively, refining multidimensional datasets to focus on specific conditions or criteria.

However, the efficacy of correlating sustainability indicators cannot be solely attributed to applying a set of constraints simultaneously. This arises due to trade-offs among various technical factors in the optimization process, leading to interdependencies between certain sets of output constraints. For example, this study identifies a fivefold interrelation among the merit variables, including emissions, renewable energy, fossil fuels, capital, and variable costs, aligning with sustainability optimization. Utilizing these variables to construct a correlation matrix may result in a biased interpretation, potentially skewing towards an ambiguously positive absolute correlation between sustainability indicators.

Furthermore, correlation matrices evaluated using simpler selection criteria demonstrate an inverse correlation between economic sustainability optimization criteria and environmental sustainability indicators. However, the latter positively correlates with the energy sustainability indicator, unless economic constraints are explicitly considered.

While economic sustainability indicators may yield rapid returns on investment and cost reduction, they may also lead to increased fossil fuel usage, higher variable costs, and elevated pollutant emissions. Consequently, economic sustainability indicators may not be suitable when primary objectives align with decarbonization efforts. This highlights a significant inherent dichotomy between economic and environmental sustainability goals, especially concerning carbon emissions reduction and climate change mitigation, alongside an increasing reliance on renewable attributes and associated investment costs.

Addressing the challenge of decarbonization requires considering both economic and environmental factors. This may entail integrating environmental sustainability criteria into economic decision-making processes using energy sustainability indicators. Although energy sustainability indicators exhibit stronger correlation with environmental sustainability, their characteristic within the cradle-to-cradle paradigm presents a balanced approach between economic and environmental factors.

In conclusion, fostering stronger alignment among economic, energy, and environmental sustainability goals often entails reevaluating the weighting assigned to different indicators within optimization functions. Explicitly prioritizing optimization objectives that promote sustainability is essential. The insights gained from the results facilitate this prioritization, allowing it to be directly incorporated into the optimization function of modeling tools. This enables decision-making that aligns more closely with the objectives of decision-makers, providing a comprehensive understanding of each indicator's behaviour concerning the considered output variables, such as energy production sources categorized by economic costs and emissions.

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