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A multiobjective optimization approach to support end-use energy efficiency policy design – the case-study of India

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ABSTRACT

We combine the use of the Economic input-output lifecycle assessment with multiobjective interval portfolio theory to arrive at two model formulations which can support public decision-makers on the design of programs to promote the investment in energy efficient technologies. Each model contains two objective functions. The first one is the maximization of the savings to investment ratio as a proxy of return maximization. The second one is the maximization of the minimum deviation of greenhouse gas avoided emissions (energy savings) of the portfolio over its lifetime from the expected greenhouse gas emitted (energy embodied) in the manufacture of its components as a proxy of risk minimization. The first and second formulations might be more suitable for countries with higher and lower emission factors regarding their electricity mix, respectively. In order to ensure a certain diversification level of the technologies to be subsidized, constraints are imposed on the maximal amount of funding assigned to the energy efficient technologies under consideration, also assuring a given energy payback time/greenhouse gas payback time. Finally, conservative (leading to a lower number of subsidized devices), aggressive (leading to a higher number of subsidized devices) and combined strategies are taken into consideration in the computation of the efficient portfolio solutions. Overall, we were able to conclude that, for the case-study under consideration, it is always worth promoting the investment in tubular fluorescent lamps and water electric pumps, while incentives to purchasing more efficient television sets, computers and refrigerators should never be considered. Additionally, the most aggressive investment options always attain a higher technical energy savings potential and a higher impact on Gross Value Added vis-à-vis the investment in business-as-usual technologies. Finally, the number of jobs generated are, as it would be expected, higher with more aggressive strategies whereas conservative strategies lead to lower job creation.

Keywords:

Multiobjective portfolio theory;
Interval Programming;
Energy efficient technologies,
Economic Input-Output Lifecycle Assessment;
Energy payback time;
Greenhouse gas payback time;

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1. Introduction

Energy efficiency (EE) is becoming an important policy tool in India to deal with the substantial growth in energy demand [1]. A report by the International Energy Agency points out that 35% of the cumulative CO_2 savings would come from end-use energy efficiency [2]. Globally, buildings and construction together accounted for 36% of final energy use in 2017 [3]. Like many developing countries, in India there has been a rapid growth of its building stock, where it accounted for 41% of its total final energy use in 2013 [4]. Therefore, the need of policy options for minimizing the energy

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Acronyms

BAT – Best available technology
BAU – Business as usual
CF - Ceiling fan
COM – Computer
E3S - Economic, energy, environmental and social
EE – Energy efficiency
EERA – Energy efficient retrofit actions
EET – Energy efficient technology
EG – Electric water heater/geyser
EPBT – Energy payback time
FR – Freezer
GDP – Gross domestic product
GHG – Greenhouse gas
GPBT – Greenhouse payback time
GVA – Gross value added
IEA – International energy agency
IO – Input-Output
LCA – Lifecycle assessment
MOLP– Multiobjective linear programming
MP – Motor pump
NAPCC – National action plan on climate change
O&M – Operation and maintenance
RAC – Room air conditioners
RES – Renewable energy systems
SIR – Savings to investment ratio
TESP – Technical energy savings potential
TFL – Tubular fluorescent lamp
WEP – Water electric pumps
WM – Washing machine

demand is equally important for India, namely promoting the adoption of EE of end-use technologies in the residential sector [5].

The National Action Plan on Climate Change (NAPCC) in India was launched in 2008 and it identified a set of measures that simultaneously accounted for the GDP's growth and climate change objectives of adaptation and mitigation [6]. The NAPCC was an initiative framed under the country's specific circumstances, especially incorporating EE concerns [7].

EE penetration in India's industries and other sectors varies widely and has an acknowledged role as an effective catalyser for reducing energy consumption and greenhouse gas (GHG) emissions, without impairing the access to energy services. Several studies focusing on EE highlight the absence of awareness/information, financial reasons, and split incentives as some important barriers to EE improvement in buildings (see e.g. [7–10]). The policies endorsing EE in the residential sector are significantly associated with energy efficient advances in buildings and lighting end-use [11].

Since EE programmes usually make use of subsidizing programs sought to elect highly efficient actions, energy policy decision-makers should have at their disposal sound optimization tools to make better informed decisions.

To our knowledge the first attempt to obtain a global overview of the impacts of some energy efficient retrofit investments through the integration of a bottom-up approach into a top-down model was made by [12]. In their work some results are reported regarding the implementation of a methodological framework for assessing the impacts of energy saving measures in the building sector based on a multiobjective linear programming (MOLP) model and on input-output (IO) analysis. Consistent estimates for depicting important impacts, namely on environment, energy security of supply and other relevant economic indicators were provided through this type of methodology. Furthermore, [13] implemented an IO methodological framework which provides estimates regarding the contribution of some energy saving measures in the Portuguese building sector (residential, private services and public services) in net employment generation.

More recently [14] also quantified the economic, environmental and social benefits of large-scale energy efficiency programs in Qatar by means of detailed parametric and optimization analyses using lifecycle cost analysis for both new and existing buildings.

Consequently, the use of traditional optimization models which rely on the single concern of cost minimization become less reasonable, thus requiring the development of more suitable optimization tools.

In this context, modern portfolio theory has been broadly employed in finance in the evaluation of electricity power assets (see [15] for a review on this topic).

From the investor's stance, portfolio theory aims at selecting the portfolios of electricity power technologies with the lowest risk and highest return, taking into consideration the economic, technical and social concerns at stake, in addition to resources scarcity [16]. In this case, [17] proposed two possible mean-variance approaches for the design of optimal renewable electricity production portfolios. The first one is aimed at maximizing the portfolio output and the second one is aimed at minimizing the portfolio cost. A set of renewable energy sources (RES) portfolios was computed, integrating three RES technologies, namely hydro power, wind power and photovoltaic (PV).

Furthermore, modern portfolio theory has also been adjusted to address other types of environmental investment problems, including in conservation investment decision cases, in agroecosystems planning, land allocation and forest management, among other fields of application. With this regard, [18] considered conservation investments which are assigned to distinct sub regions of a planning area. The percentage of the total portfolio investment in a particular sub region is viewed as that sub region's weight. The portfolio model thus considered computes the portfolio weights that minimize the variance of the total ecological value of the chosen investments for a given expected value of the portfolio. This optimization problem is then solved for multiple levels of expected ecological value (or return) in order to compute a set of efficient portfolios. [19] suggested a portfolio optimization model which covers three sustainability dimensions: the economic sphere, given as the maximization of the average annual income over the considered time horizon, defined as the average net present value of the yearly revenue from the agricultural production; the maximization of biodiversity referring to the portions of available area occupied by each species; and the social dimension of sustainability, given by the stability of annual economic income, as a proxy for the economic risk considered as the minimization of the monthly income variance within a year. [20] dealt with scarce land to various land-use options by means of portfolio theory, which proposes a variant of robust portfolio optimization as an alternative to the classical stochastic mean-variance optimization model that requires less pre-information. In their model, the maximization of the economic return of the land-use portfolio is subject to a set of constraints that impose that a pre-defined return threshold is reached by the robust solution for each uncertainty scenario considered. [21] also used modern portfolio theory in the appraisal of the risks and returns related with payments for ecosystem services (PES) for private forestland. In this study, PES schemes for biodiversity conservation and climate change mitigation were explicitly addressed.

Additionally, portfolio optimization theory has also been used to support public bodies in investment planning for EE programs (see e.g.[22-23]), although less abundant publications still exist on this topic.

It becomes clear from the literature review that comprehensive approaches which encompass environmental and socioeconomic concerns are viewed as fundamental pillars in the design of more sustainable energy efficiency programmes.

In this context, IO analysis can be regarded as a suitable methodological technique for the assessment of the inter-relations among distinct industrial sectors, which has been applied to assess economic, energy, environmental and social (E3S) interactions [24]. Therefore, despite the limiting hypotheses inherent to the application of the IO approach, specifically the assumption of the constancy of the model's coefficients, the level of data aggregation and the fact that it does not include any mechanism for price adjustments, an essential interest of IO analysis is associated with the possibilities of its practical application. In fact, on the one hand, the importance of the IO Leontief approach comes from its ability of depicting the technology and its changes with sufficient precision to allow presenting a real empirical analysis [25]. On the other hand, IO analysis entails structural information and satisfies a number of laws and identities of conservation, namely general interdependency. Furthermore, IO analysis is an adaptable tool for theoretical or empirical studies of a broad range of problems, which enables assessing any type of environmental burden caused by changes in the output of industrial sectors once reliable economic data is used.

Therefore, taking India's residential sector as a case study, this work is aimed at suggesting a new modelling tool to support public investors in the appraisal and selection of distinct energy efficient technologies (EET) based on portfolio theory combined with IO analysis.

This work provides new fertile grounds for this field of application, in particular: 1) we have adapted the energy payback time (EPBT) and the greenhouse gas payback time (GPBT) indicators typically used in lifecycle assessment (LCA) to quantify the energy consumption and GHG emission patterns of each EET, respectively, based on national IO data different from the approach normally found in traditional lifecycle inventories; 2) then, besides the traditional EPBT and GPBT which only account for direct energy saving effects, new EPBT and GPBT concepts are introduced which consider both indirect and induced energy savings and GHG emission effects; 3) we suggest a new multiobjective interval optimization portfolio (MIOP) framework which encompasses new surrogate measures of return and risk minimization based on the EPBT and GPBT concepts previously developed; 4) finally, a comprehensive assessment of the anticipated E3S impacts regarding the adoption of the different portfolios selected according to distinct model formulations is also provided.

The remaining of this paper is structured as follows. Section 2 presents the approach herein followed to arrive at EPBT and GPBT, the underpinning assumptions to the MIOP model formulation and the methods to obtain the possibly efficient portfolios according to the investor's strategies. Section 3 delivers the main assumptions concerning data collection. In Section 4 the main outcomes of this study are conveyed. Finally, in Section 5 the main conclusions are drawn, and possible future research opportunities are also indicated.

2. Methodology

In this Section, a brief description of the necessary adjustments required to obtain the EPBT and GPBT in the framework of the IO approach is provided (see Appendix[2] A for further explanations regarding the IO methodology). The underpinning assumptions and notations considered in the model formulations herein developed are also described (for further details on the interval programming approach see Appendices B and C). Moreover, a comprehensive presentation of the objective functions and constraints used in the MIOP models is also given. Finally, distinct surrogate mathematical models are proposed according to distinct investor's standpoints.

Figure 1 portrays a schematic representation of the main steps followed in the application of the methodological framework herein proposed.

2.1. Energy Payback Time and Greenhouse Gas Payback Time

The EPBT is an indicator used in LCA which has been applied in several studies in the evaluation of the energy obtained through RES, such as photovoltaic systems [26–31] , wind power [32], fuel cell stacks [33] and biofuel [34].

This type of metric can be adjusted to encompass the evaluation of energy efficient retrofit actions (EERA) [35, 36, 37]. In this framework, the GPBT can also be helpful since it allows expressing the GHG mitigation potential of EERA [38]. When considered in the context of RES, the EPBT is mainly dependent on the energy incorporated in the manufacture of its components [39]. In fact, the EPBT is the time (in years or months) required to regain the total energy invested in the manufacture of the materials incorporated into RES (i.e. embodied energy) and it is given by the ratio of embodied energy to annual energy output from the system [40]. Embodied energy inputs usually include the energy requirements in different stages that go from manufacturing, to installation, energy use during operation and maintenance (O&M), eventually considering the energy demanded for decommissioning, while the energy output corresponds to the annual energy avoided from other sources due to electricity generated from RES [26].

The application of the EPBT in the particular case of EERA is the time (in years or months) needed for the retrofit action to recuperate the total energy spent in the manufacturing of the materials used in it and it is the ratio of the embodied energy to the annual energy savings obtained [31]. When applied to the assessment of EERA, the EPBT should also consider the energy used in the deployment and installation of the device, additionally to its embodied energy. The EPBT will, thus, allow to assess to what extent energy savings compensate all the upstream energy used, up to the moment when the device is ready to provide the energy service for which it was designed.

In our analysis we have followed the Economic IO LCA approach (for further details see Appendix A) which is a methodological framework sought to simplify LCA based on an IO matrix with the economic flows between industries that can be extended with information regarding the environmental discharges to the environment, creating additional columns and rows that

[2] All the appendices of this paper are available at: http://dx.doi.org/10.5278/ijsepm.2408

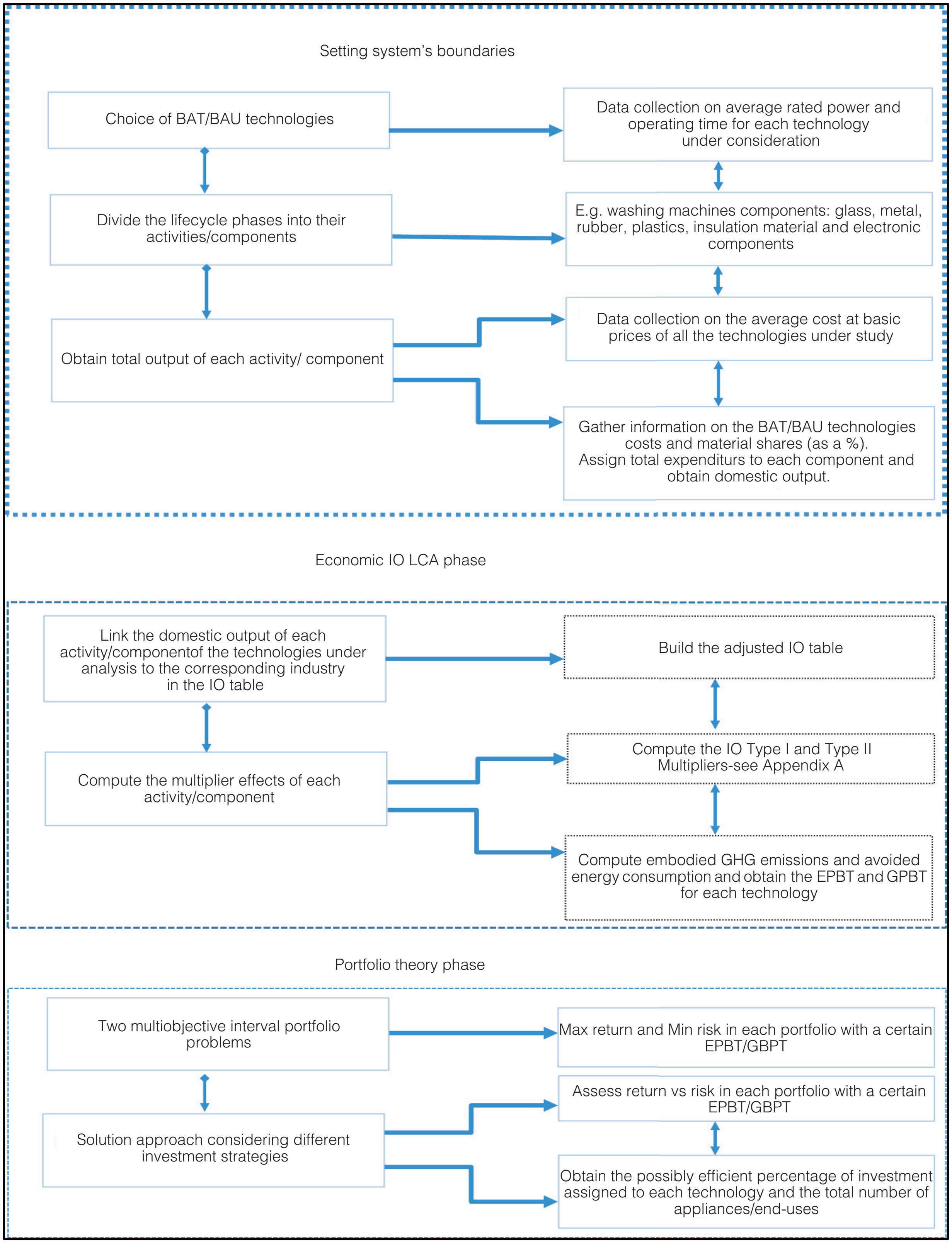


Figure 1: Steps followed in the application of the methodological framework proposed

represent the environmental impacts per each activity sector/industry [41, 42].

Nevertheless, the use of the Economic IO LCA approach in the framework of EERA also involves a challenging exertion, since the IO tables officially published do not possess the required detail to identify the prospective economic impacts that can be attained because of the demand for a typical best available (BAT) or business as usual (BAU) technology. In this context, the disaggregation of the EERA's components is not straightforward, requiring the explicit use of supplementary data, exogenous to the information provided in currently available IO tables. Hence, following the methodology given in [42] – see Figure 1 – the lifecycle of each BAT/BAU technology has been divided into their related activities/components.

2.2. The portfolio optimization problem with interval coefficients

Consider that the public decision-makers are interested in subsidizing n EET and that energy savings per unit funding invested is a proxy of return [23].

Portfolio selection problems are usually specified as biobjective optimization problems that seek to attain an acceptable compromise between the expected rate of return and risk [43].

In here, we consider that the risk of adopting an EET is gauged by the risk of the energy savings (GHG avoided) obtainable during the lifetime of the technology not compensating the energy use (GHG emitted), i.e. the embedded energy (embedded GHG) in the manufacturing and deployment of that technology [23].

Young [44] proposed as an alternative measure for risk the maximization of the minimum return (or minimization of the maximum loss) demanded by the investor. This risk measure is relatively simple, but some authors argue that it might lead to an infeasible solution if all assets yield a negative return. However, only occasionally, an ill-conceived EERA intervention could cause a higher lifetime energy consumption, making the overall energy saved negative. Hence, the risk measure herein tackled is the maximization of the minimum deviation of energy savings (GHG emissions avoided) of the portfolio from the corresponding energy (GHG emissions) embodied in it.

Therefore, the following problem is obtained:

$$\begin{aligned}
&\max\min \sum_{i=1}^{n}\left[r_{iT}^{L},r_{iT}^{U}\right]x_i-\sum_{i=1}^{n}\left[r_i^{L},r_i^{U}\right]x_i,\\
&\max \sum_{i=1}^{n}\left[SIR_i^{L},SIR_i^{U}\right]x_i,\\
&s.t: \sum_{i=1}^{n}x_i=1,\\
&\sum_{i=1}^{n}y_i\le\left[h^L,h^U\right],\\
&y_iGPBT_i\le\left[GPBT_i^L(\text{or } EPBT_i^L),GPBT_i^U(\text{or } EPBT_i^U)\right], i=1,\ ...,n,\\
&x_i\le[u_i^L,u_i^U]y_i,\ i=1,\ ...,\ n,\\
&x_i\ge 0, i=1,\ \ldots,\ n,\\
&y_i\in\{0,1\}, i=1,\ \ldots,\ n.
\end{aligned}\tag{1}$$

where x_i is the percentage of funds allocated to the i^{th} EET; y_i is a binary variable discriminating the ith EET belonging to the portfolio; $[r_{iT}^L,\ r_{iT}^U]$ refers to the projected energy savings or GHG emissions avoided across the lifetime of the EET i per unit funding invested (an interval value), respectively (depending on the mathematical formulation considered); $[r_i^L,\ r_i^U]$ are the energy or GHG emissions embodied in the i^{th} EET per unit budget input, respectively (depending on the mathematical formulation selected); SIR is the savings to investment ratio which is also given as an interval value, where $SIR_i^L \frac{\sum_{t=1}^{T}\frac{ES_{it}}{(1+d^U)^t}}{I_i^U}$ and $SIR_{i=}^U \frac{\sum_{t=1}^{T}\frac{ES_{it}}{(1+d^L)^t}}{I_i^L}$ are the lower and upper bounds of the savings to investment ratio, d^L and d^U are the lower and upper bounds of the discount rates (reflecting lower and higher opportunity costs, respectively) and I_i^L and I_i^U are the lower and upper values of the level of public support regarding the investment in energy efficient projects; $[h^L,\ h^U]$ is an interval range of the number of EET the public investor wants to consider in the portfolio; the upper acceptable limits to the EPBT and GPBT are considered within the intervals $[EPBT_i^L,\ EPBT_i^U]$ and $[GPBT_i^L,\ GPBT_i^U]$, respectively (according to the mathematical model used); the upper bounds on the investment in each EET are also given within a range of values, $[u_i^L;\ u_i^U]$, and y_i is a binary variable that allows identifying if the BAT i either belongs to the portfolio (i.e. assuming the value "1" if it belongs or "0" if it does not belong to the portfolio).

Let v be the minimum difference between the energy savings across the lifespan of a portfolio of lighting projects and the corresponding energy incorporated in it, such that $v = \min \sum_{i=1}^{n} \left[r_{iT}^{L}, r_{iT}^{U} \right] x_i - \sum_{i=1}^{n} \left[r_i^{L}, r_i^{U} \right] x_i$. The risk function maximizes the minimum gain (i.e. minimizes de maximum loss) or alternatively it maximizes v, where $\sum_{i=1}^{n} \left[r_{iT}^{L}, r_{iT}^{U} \right] x_i - \sum_{i=1}^{n} \left[r_i^{L}, r_i^{U} \right] x_i \geq v$. This last equation guarantees that v will be upper bounded by the minimum portfolio gain; because this is the only constraint on v and since v is being maximized, it will take on the value of the maximum minimum gain, or the minimum maximum loss. Then, problem (1) has the following surrogate multiobjective interval integer linear programming problem:

$$
\begin{aligned}
&\max v, \\
&\max \sum_{i=1}^{n} \left[SIR_i^{L}, SIR_i^{U} \right] x_i, \\
&s.t: \sum_{i=1}^{n} x_i = 1, \\
&\sum_{i=1}^{n} y_i \leq \left[h^{L}, h^{U} \right], \\
&y_i GPBT_i \left(\text{or } EPBT_i \right) \leq \left[GPBT_i^{L}\ GPBT_i^{U} \right] \left(\text{or } \left[EPBT_i^{L}\ EPBT_i^{U} \right] \right), i=1, \ldots, n, \\
&\sum_{i=1}^{n} \left[r_{iT}^{L}, r_{iT}^{U} \right] x_i - \sum_{i=1}^{n} \left[r_i^{L}, r_i^{U} \right] x_i \geq v, \\
&x_i \leq [u_i^{L}, u_i^{U}] y_i, i = 1, \ldots, n, \\
&x_i \geq 0, i = 1, \ldots, n, \\
&y_i \in \{0,1\}, i = 1, \ldots, n.
\end{aligned}
\tag{2}
$$

2.3. The solution approach

Problem (2) can be straightforwardly replaced with a surrogate linear interval objective optimization problem through the weighted-sum method [42]. Distinct optimization models for portfolio selection can thus be considered following different kinds of investment standpoints, namely, a conservative strategy (leading to a lower number of subsidized devices), an aggressive strategy (leading to a higher number of subsidized devices) and a combined strategy.

$$
\begin{aligned}
&\max \rho(\beta \sum_{i=1}^{n} SIR_i^{L} x_i + \alpha v) + (1-\rho)(\beta \sum_{i=1}^{n} SIR_i^{U} x_i + \alpha v) \\
&s.t: \sum_{i=1}^{n} x_i = 1, \\
&\sum_{i=1}^{n} y_i \leq h^{U} - \delta(h^{U} - h^{L}), \\
&y_i GPBT_i (\text{or } EPBT_i) \leq GPBT_i^{U} (\text{or } EPBT_i^{U}) \\
&\quad - \mu_i (GPBT_i^{U} (\text{or } EPBT_i^{U}) - GPBT_i^{L} (\text{or } EPBT_i^{L})), i = 1, \ldots, n, \\
&\sum_{i=1}^{n} ((r_{iT}^{U} - r_i^{L}) + \varpi((r_{iT}^{L} - r_i^{U}) - (r_{iT}^{U} - r_i^{L}))) x_i \geq v, \\
&x_i \leq (u_i^{U} - \delta_i(-u_i^{L} + u_i^{U})) y_i, i = 1, \ldots, n, \\
&x_i \geq 0, i = 1, \ldots, n, \\
&y_i \in \{0,1\}, i = 1, \ldots, n,
\end{aligned}
\tag{3}
$$

where $0 < \beta,\ \alpha < 1$, are weights which indicate the decision-maker's preferences regarding each objective function, and ρ, δ, μ_i, ω and δ_i are indexes of pessimism varying on a scale from 0 (an aggressive strategy) to 1 (a conservative strategy).

3. Data and Assumptions

We have used the national IO tables for India available from the World IO Database to appraise the energy and environmental impacts of several EET in India's residential sector (see [45] and [46]). The year 2011 was selected to be the base year of our study since the methodology herein developed is based on the classification of households considered in the latest Census published by the Government of India which dates back to 2011. Distinct data sources have also been used in order to set up a large size structured repository of real data for India's residential sector (see, e.g. [47–57]). Tables D1 and D2 (Appendix D) provide specific information regarding the features of each technology under evaluation and the average annual operating hours according to the average operation data available for India, the lifetime and the investment cost of each EET under analysis. Table D3 (Appendix D) provides the average shares of materials and the costs considered for each BAT, which were based on [42]. Finally, the energy balances of India have also been used to account for the energy consumption and then they were coupled with the World IO Database.

4. Illustrative Results

Since the EPBT is linked to the yearly useful energy saved by the EET under analysis, while the GBPT depends on the emission factors of the electricity mix within the country, two distinct formulations were herein considered. These modelling formulations either account, respectively, for the embodied GHG emissions or the embodied energy during the manufacturing phase, which are mainly dependent on the manufacturing processes and on the availability of the raw materials [52–53].

Therefore, the modelling framework suggested is consistent with the EE policies which usually address the residential sector in developing countries, where the promotion of the investment in appliances with low embodied energy [54] and low embodied CO_2 emission [55] is particularly relevant.

While the formulation relying on the maximization of the minimum deviation of the GHG avoided emissions from the GHG embodied emissions might be more helpful for countries with higher emission factors regarding the electricity mix within the country, the second formulation which accounts for the maximization of the minimum deviation of the energy savings from the embodied energy might be more useful for countries with lower emission factors regarding their electricity mix.

4.1. Max min deviation of avoided emissions from embodied emissions

The solutions herein presented were obtained by considering $[EPBT_i^L, EPBT_i^U] = [1.13, 2.30]$, i.e. the EPBT should be below the average EPBT of the technologies under assessment in a conservative strategy and below the greatest EPBT if an aggressive strategy is assumed.

The maximum number of technologies being held in the portfolio is assumed to be $[h^L, h^U] = [4, 5]$, while the maximum funding allocated to each technology is $[u_i^L, u_i^U] = [25\%, 50\%]$, in order to ensure a certain level of diversification.

The number of devices targeted for funding in India (Table E1 b), d) of Appendix E) can be computed both considering as a reference the World EE investment as a percentage of GDP which was about 0.3% in 2016, according to the IEA EE Market Report published in 2016 [56] and World Energy Investment 2017 [57] and to the STATISTA - The Statistics Portal [58] and the share of energy consumption by the residential sector in India, which was about 25% in 2015 [59]. This allowed us to estimate that a reasonable investment value on EET would be 1,466 million dollars at constant prices of 2011.

The results depicted in Figure 2 a), b) illustrate the consistency of the strategy type considered with the level of risk assumed by a certain decision maker (higher return corresponding to a higher risk solution, i.e. a solution with a higher number of subsidized devices and vice-versa).

Table E1 a) and b) provides information regarding the EET chosen in each solution (although other search strategies could be considered).

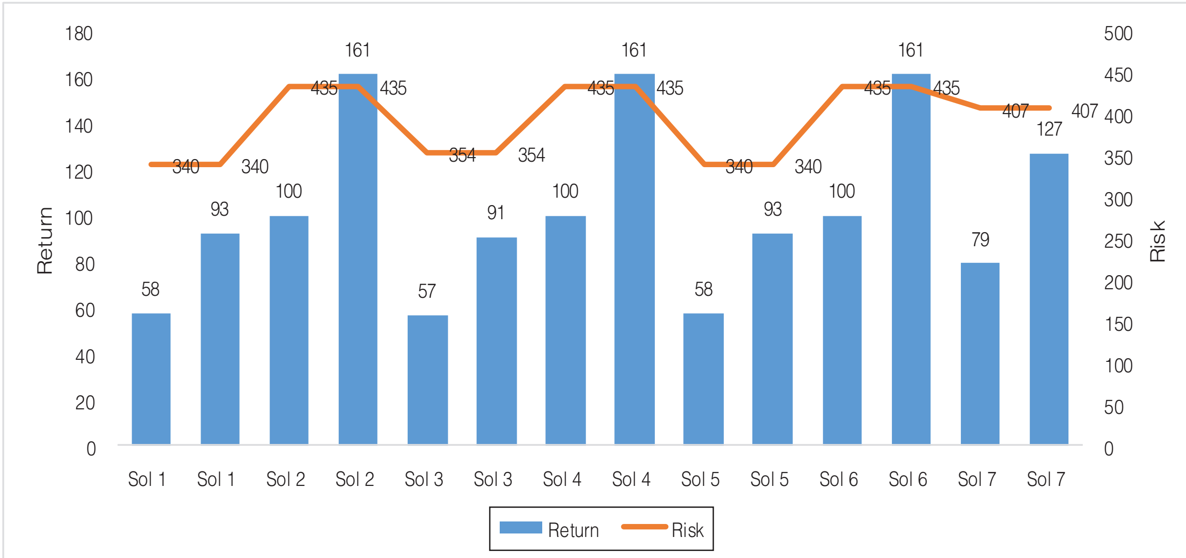
Figure 2 a) presents the values obtained for return (SIR) and risk in each portfolio. Under this formulation the trade-off between risk and return is reduced.

Several conclusions can be gathered based on a certain EPBT:

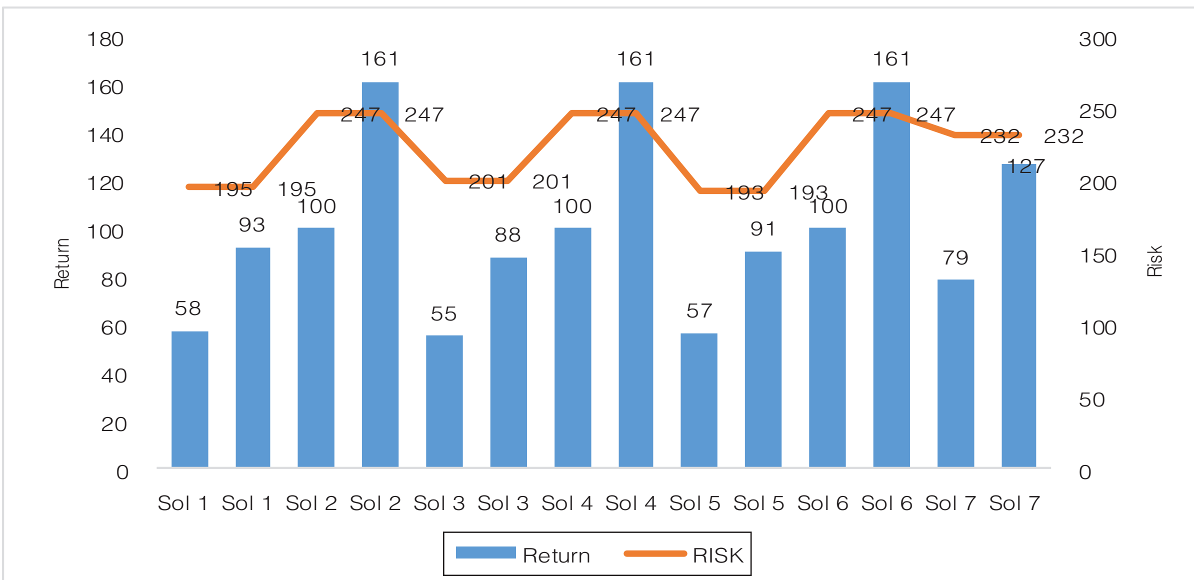
1) Aggressive strategies always lead to less diversified portfolios with similar solutions both for the individual optimization of return and risk, respectively. In this situation (solutions 2, 4 and 6), the funding is evenly distributed between TFL (suggesting the replacement of 363.8 million of lamps) and WEP (proposing the substitution of 59.4 million of water pumps). The highest performance of TFL and WEP both regarding the SIR and the highest difference between embodied emissions regarding avoided emissions justify these results (Table D4).
2) Conservative strategies always lead to the most diversified portfolios, but with distinct technology choices for return and risk. In the maximization of return (solution 1) the portfolio contains TFL (139.1 million lamps), RAC (2.6 million devices), WM (4.7 million machines) and WEP (22.7 million water pumps), while in risk optimization (solution 3) the portfolio incorporates EG (12.6 million devices), TFL (139.1 million lamps), WM (4.7 million washing machines) and WEP (22.7 million water pumps). Under this conservative scenario it is interesting to see that TFL, RAC and WEP are considered as a good investment option in both cases.
3) Under a conservative strategy, if both risk and return have the same weight, solution 5 is different from solution 1, replacing the investment in WM with the investment in CF (28.7 million ceiling fans); in contrast, a balanced approach towards risk and return under an aggressive strategy (solution 6) allows obtaining the same portfolio of solutions 2 and 4.
4) A combined approach with average pessimistic coefficients (solution 7) leads to the even investment in TFL (239.6 million lamps) and WEP (39.1 million pumps) (37.5% of investment allocated to each technology), while WM (4.7 million washing machines) takes 25% of the investment.
5) According to this modelling formulation, TV, FR and COM are never selected for a public program for supporting EET (Table E1a)).

4.2. Max min deviation of energy savings from the embodied energy

The solutions herein computed were obtained by considering $[GPBT_i^L, GPBT_i^U]$=[2.65, 4.13], i.e. the



a) Return vs risk with a certain EPBT



b) Return vs. risk with a certain GPBT

Figure 2: Return vs. risk obtained in each portfolio with a certain EPBT/GPBT

GPBT is considered to be below the average GPBT of the technologies under assessment in a conservative strategy and below the greatest GPBT if an aggressive strategy is considered. The maximum number of technologies being held in the portfolio and the maximum funding allocated to each technology are identical to the previous formulation.

Figure 2 b) presents the values computed for return (SIR) and risk in each portfolio. Under this formulation the trade-off between risk and return is reduced.

Table E1 c) and d) provides information regarding the EET selected according to distinct strategies (other search strategies could also be investigated). Based on a certain GPBT several conclusions can be drawn:

1) Once more, aggressive strategies always lead to the less diversified options with similar technology portfolios for return and risk (solutions 2, 4 and 6), equally suggesting TFL and WEP for funding (the same results were also attained with the previous formulation).

2) Conservative strategies always lead to the most diversified policies, but once more with distinct technology portfolios for return and risk. In solution 1 (maximization of return) the portfolio contains TFL, RAC, WM and WEP (the same results were also obtained with the previous formulation). In solution 3 (maximization of the minimum deviation of the energy saved regarding the energy embodied during the manufacturing stage) the selected appliances differ from the previous ones because the portfolio now includes CF (28.7 million of fans) instead of EG. When compared to solution 3, if both risk and return have the same weight, solution 5 leads to include WM (4.7 million washing machines) and RAC (2.6 million devices) in the portfolio, instead of CF.
3) The solution obtained with this formulation with a combined approach (solution 7) leads to a different portfolio than the one obtained under the same assumptions with the previous formulation, replacing the investment in WM with the investment in RAC.
4) According to this modelling formulation, EG, TV, FR and COM appliances are never selected under the auspices of a public program for supporting EET (Table E1c)).
5) Overall, it can be concluded that it is always worth endorsing the investment in TFL and WEP with both modelling formulations. Finally, the promotion of more efficient TV, FR and COM is never considered in both modelling formulations.

Indices of robustness have also been computed, which allow assessing the technologies which are more often selected irrespective of the investment strategy followed – see Tables E2 and E3 (Appendix E). According to the values obtained, TFL and WEP should have the highest support in terms of funding no matter the DM's stance or the modelling formulation considered. The investment in CF, RAC and WM should also be contemplated in terms of support with both modelling formulations. The investment in EG should be considered when a certain EPBT is imposed, while the investment in CF is only selected if a certain upper bound on GPBT is introduced (following the most conservative strategies). Finally, TV, COM and FR should never be considered in terms of support for funding with either formulation.

Further information on the evaluation of the anticipated E3S impacts regarding the adoption of the different BAT selected in each portfolio is given in Appendix F.

5. Conclusions

In this paper a methodological tool developed to help public decision-makers in the choice of several EET to be subsidized in India's residential sector is presented, which can help shaping the design of EE programs in this country. A new overarching framework was also suggested for obtaining the EPBT/GPBT for EET based on the Economic IO LCA approach, which allows assessing the direct, indirect and induced EPBT/GPBT of BAT technologies. The importance of this new EPBT/GPBT modelling structure might be ascertained by the fact that positive direct effects regarding the adoption of EET can be overcompensated by indirect impacts on other activity sectors, in particular in the upper industrial supply chain.

The fact that the energy/GHG incorporated in each EET under consideration has been obtained through the use of India's national IO data, enabling to overcome one of the major drawbacks regarding truncation problems typically encountered when an approach based on the traditional lifecycle inventories is followed, is one of the main advantages of this new modelling proposal.

Based on the data obtained, it was possible to establish that the EPBT for domestic BAT appliances in India is always lower than the corresponding expected lifetime. Although opposed conclusions were drawn regarding several renewable electricity systems, namely for PV [26-31],wind power [32] and fuel cell stacks [33], our results are consistent with the ones obtained for low concentrating solar PV-thermal (CPVT) systems [60] and for several EERA [36]. Overall, the EPBT relies on the yearly ratio (energy consumed/yearly energy saved) by the system under analysis, while the GBPT is mainly explained by the emission factors of the electricity mix within the country.

Two modelling formulations based on interval portfolio theory were also proposed, where the objective functions used are adapted to the appraisal of distinct EET generally held in India's residential sector. The objective functions which allow evaluating the trade-off between the return and risk of the portfolio of EET are the SIR and the maximization of the minimum deviation of the energy savings (GHG avoided emissions) of the portfolio from the expected energy embodied (GHG emissions) in the materials used for its manufacture, respectively. The diversification of the portfolio is ensured by the consideration of upper bounds on the maximal funding that can be assigned to the various EET also imposing a given EPBT/GPBT.

The selected portfolios of EET were then obtained by developing different surrogate problems reflecting distinct investment standpoints, i.e., a conservative strategy (leading to a lower number of subsidized devices), an aggressive strategy (leading to a higher number of subsidized devices) and a combined strategy.

Based on the results computed, some guidelines can be drawn to help and support energy decision planning and energy decision-makers, in particular in a context where BAT technologies are designed to reduce energy consumption, bringing to light the need to consider a lifecycle approach in their performance assessment. In general, it can be concluded that it is always worth promoting the investment in TFL and WEP, while the incentive of more efficient TV and FR should never be considered, according to both modelling formulations.

Additionally, the assessment of the anticipated E3S impacts regarding the adoption of the different BAT selected in each portfolio was also conducted. With this regard, the most aggressive investment options always attain a higher TESP. Furthermore, the formulation which uses a given EPBT usually results in a higher TESP under the conservative investment options when contrasted with the formulation which uses a certain GPBT. In what concerns the economic impacts, the investment in BAT has a higher impact on GVA vis-à-vis the investment in BAU technologies. Then again, the most aggressive investment options are those which allow reaching the highest GVA. In terms of environmental impacts, both model formulations lead to quiet similar results. Lastly, concerning the analysis of the social impacts, the number of jobs generated are, as it would be expected, higher with aggressive strategies whereas conservative strategies lead to lower job creation.

It should be stressed that future work should be developed in order to encompass the assembly and disposal phases of the equipment as well. Furthermore, while the study behind this paper specifically addresses energy efficient technologies in India's residential sector, this work may be used to inspire similar approaches in commercial and industrial sectors. In addition, because of the scarcity of data available, namely regarding the material cost shares of each technology, future work is needed to reduce the uncertainty raised by this type of shortcomings, namely by considering other possible hybrid IO LCA frameworks.

Finally, it should be noted that the use of IO data also leads to a static consideration of technology evolution, both on the supply and on the demand sides of the energy value chain: in fact, aspects such as the trend to always increasing efficiencies of end-use equipment and the evolution of the generation mix are not captured by the model.

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