

Supporting public decision-makers in the design of energy efficiency programs: A portfolio based approach

Carla Henriques^{1,2*}, Dulce Coelho^{2,3}, Maria Elisabete Neves^{1,4}

¹*Polytechnic Institute of Coimbra - ISCAC, Portugal*

²*INESC Coimbra – Portugal*

³*Polytechnic Institute of Coimbra - ISEC, Portugal*

⁴*CETRAD-UTAD, Vila Real*

**Corresponding Author: chenriques@iscac.pt*

Abstract

This paper aims at developing a methodological framework to support public authorities in investment planning for energy efficiency programs based on portfolio theory explicitly considering the energy spent in the manufacturing and installation of each energy efficient technology. The applicability of the methodology herein proposed is illustrated by considering the potential investment in distinct portfolios of industrial lighting systems. Finally, a new solution methodology for computing possibly efficient solutions is also suggested which allows exploring distinct types of investment strategies, according to the public investor's preferences.

Keywords: Multiobjective interval portfolio programming, Energy efficient lighting systems, Economic Input-Output Life-cycle Assessment, Energy payback time

1 Introduction

The International Energy Agency anticipates that by 2030 one half of the lowest-cost greenhouse gas (GHG) emission abatement options in the Organization for Economic Cooperation and Development member countries will come from the adoption of energy efficient (EE) end-use technologies (International Energy Agency, 2015). In this context, the promotion of energy efficiency policies can be considered as a cost-effective means for reducing both energy consumption and GHG emissions, while guaranteeing quality energy services in various industrial activities.

Since energy efficiency standards are aimed at reducing the energy requirements during the operation phase, the progress of energy technologies towards low energy use gives the embodied phase a prominent role when considering the life-cycle of the equipment. Hence, in order to reduce both the energy use and the environmental impacts associated to EE technologies it is crucial to follow a life-cycle perspective. In this framework, Life-cycle analysis (LCA) can be used to identify the most critical components of the environmental performance of existing technologies and to evaluate the potential benefit of different energy technologies. Nevertheless, traditional LCA can be time, data, and resource intensive. In order to overcome these limitations, hybrid input-output (IO) LCA frameworks should rather be used (see e.g. Carvalho et al. (2016) and Singh et al. (2018)).

Currently, the Portuguese Energy Efficiency Action Plan (NEEAP) typically exerts subsidy programs aimed at funding highly efficient measures (Portuguese Government, 2013), requiring that energy decision-makers are sustained by sound optimization frameworks to reach better-informed decisions. The 'California Standard Practice Manual' is usually followed in the support of energy efficiency programs that provide funding to EE technologies. However, this type of approach presents several weaknesses lacking an overall integrated and holistic assessment.

Portfolio optimization theory has been broadly used in several environmental contexts, and it can also be adjusted to support the choice of the EE projects to be funded by public decision-makers, despite publications with this sort of applications remain less abundant (see e.g. Lee et al. (2013) and Henriques and Coelho (2017)).

With the foregoing in mind, this study is aimed at suggesting a modelling framework which can be of help for public decision-makers in the choice and evaluation of the EE measures that can be adopted in industrial buildings, coupling portfolio theory with hybrid IO LCA methodologies. Since, in spite of their importance, industrial lighting systems tend to be overlooked (Portuguese Government, 2013), the usefulness of the proposed approach will be illustrated in the choice and evaluation of the EE lighting portfolios that should be targeted for funding/support by public decision-makers.

The remaining of this paper is structured in the following way: in Section 2 we provide a description of the methodological framework herein developed; Section 3 conveys the main premises regarding data gathering; in Section 4 a brief discussion of some computed illustrative results is presented; finally, some conclusions are stated and future work improvements and directions are suggested.

2 Methods

In this Section, some of the underpinning assumptions regarding the computation of the energy payback time (EPBT) based on the Economic IO LCA (EIO-LCA) approach are described. The Multiobjective Linear Programming (MOLP) models with interval coefficients that will be used are also provided, explaining the

underlying hypotheses for the choice of the objective functions and the constraints considered. Finally, three distinct surrogate mathematical models are obtained according to different investor's standpoints.

2.1 The Energy Payback time

The evaluation of the energy performance of renewable electricity sources (RES) generally considers the EPBT, being mainly applied to evaluate photovoltaic systems installations (Piano and Mayumi., 2017) and wind power (Zhang et al., 2017). Nevertheless, this type of metric has similarly been used in the appraisal of EE retrofit interventions (Ardente et al. 2011); (Dutil and Rousse, 2012). The EPBT measures the time that it takes to restore the energy spent in the manufacture of RES/EE technologies through the energy produced/saved (per year). In the case of EE technologies, the energy spent should only involve the energy needed to implement or install the solution and it should not consider the energy consumed by the equipment itself (Ardente et al. 2011).

In order to overcome the gaps typically noticed on traditional life-cycle inventories, the energy incorporated in each efficient lighting system herein considered has then been calculated through the EIO-LCA approach.

Following the idea suggested in Henriques and Coelho (2017), the EPBT, in years, for each EE project can be obtained according to:

$$EPBT_i = \text{Espenti} / \text{Esaved}_i \quad (1)$$

where Espenti is the energy incorporated during the manufacturing and installation stages of EE project i which is computed through the EIO-LCA approach and Esaved_i is the energy savings computed per year of EE project i.

2.2 The EIO-LCA approach

The EIO-LCA model uses an IO table which depicts the economic transactions among industries that can encompass other sorts of information, by adding new columns and rows that correspond to the energy used per each industrial sector (Hendrickson et al., 2006).

In its matrix form, the national productive system can be given by (Miller and Blair, 2009):

$$\mathbf{x} = \mathbf{Ax} + \mathbf{y}, \quad (2)$$

where A is the technological coefficient matrix, y is the final demand vector (households, government, firms and foreign countries) and x is the output vector.

The energy consumed by inter-industrial activities is obtained through the use of a direct coefficient matrix, E, where each component, e_{kj}, corresponds to the quantity of energy of type k spent per output unit of each industry j (Hendrickson et al., 2006). Therefore, the level of energy use intertwined with a certain output vector is:

$$\mathbf{e} = \mathbf{Ex}, \quad (3)$$

where e is the vector of each type of energy directly and indirectly consumed by the economy in supplying a certain final demand level:

$$\mathbf{e} = \mathbf{E}(\mathbf{I} - \mathbf{A})^{-1}\mathbf{y}, \quad (4)$$

From (4), E(I – A)⁻¹ can be regarded as the matrix of total energy usage coefficients. In fact, each component of this matrix provides the energy used per monetary unit of final demand.

The induced effects, referring to the impacts of money inflows and outflows of households on industries, are obtained by closing the model through the consideration of the household sector as a supplementary activity sector. This implies adding new rows and columns in the IO model, one regarding the 'compensation of employees' and another one for 'household expenditures', respectively.

Finally, it is also known that published IO tables do not enable the direct evaluation of lighting technologies. Hence, it is necessary to disaggregate these lighting technologies into their distinct constituents and related costs, and then to connect these to the industrial activities framed in the IO table and compute the pertinent energy coefficients and multipliers that will deliver the incorporated final energy in the manufacturing and installation stages of each lighting project under scrutiny.

2.3 The multiobjective interval optimization portfolio problem

The information required to instantiate multiobjective portfolio models is seldom incomplete and experts' opinions might change. Hence, besides encompassing multiple axes of evaluation, these problems should inherently involve ways to handle inexactness and uncertainty issues. Stochastic, fuzzy and interval programming techniques are some of the uncertainty handling tools typically found in scientific literature. The stochastic approach involves the treatment of the coefficients as random variables with known probability distributions. The fuzzy approach implies the use of fuzzy sets with known membership functions. Nevertheless, the decision-maker (DM) might not be able to provide these probability distributions and membership functions. In the interval approach the uncertain values are perturbed simultaneously and independently within known fixed ranges (Oliveira and Antunes, 2007). Therefore, in practice, from the point of view of the DM it might be preferable to define portfolio parameters in terms of intervals.

Interval objective functions

Interval Return. Consider that the savings to investment ration (*SIR*) is assumed to vary within an interval range, reflecting the possibility of considering different scenarios both regarding the percentage of subsidies attributed to each lighting project and distinct opportunity costs (i.e. discount rates). Hence, the objective function regarding returns assumes the form of an interval valued objective function given as:

$$(5) \quad \max \quad \sum_{i=1}^n [SIR_i^L, SIR_i^U] x_i$$

where $SIR_i^L = \frac{\sum_{t=1}^T \frac{ES_{it}}{(1+d^L)^t}}{I_i^L}$ and $SIR_i^U = \frac{\sum_{t=1}^T \frac{ES_{it}}{(1+d^U)^t}}{I_i^U}$ are the lower and upper bounds of the savings to investment ratio, ES_{it} is the energy savings per year (in €) based on electricity generation costs, d^L and d^U are the lower and upper bounds of the discount rates (reflecting lower and higher opportunity costs, respectively), 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 and x_i is the percentage of money awarded to lighting project i .

Interval Risk. We consider the risk of selecting an EE lighting project which does not compensate through the energy savings obtained during its lifespan the energy embodied in its manufacturing and installation stages. In the context of traditional portfolio theory, Young (1998) proposed the maximization of the minimum return (i.e. minimization of the maximum loss) demanded by the investor as a measure for risk. Therefore, the interval risk measure becomes:

$$(6) \quad \max \quad \min \sum_{i=1}^n [r_{iT}^L, r_{iT}^U] x_i - \sum_{i=1}^n [r_i^L, r_i^U] x_i,$$

where the projected energy savings across the lifespan of each lighting project i per subsidised monetary unit (TJ/€) are assumed to lie in interval $[r_{iT}^L, r_{iT}^U]$, depending on the subsidised amount considered, while the energy incorporated in the manufacturing and installation of each lighting project i per subsidised monetary unit (TJ/€) is given by the interval $[r_i^L, r_i^U]$, also varying with the subsidised amount used.

Interval constraints

Imposition of a minimum interval EPBT. If the maximum levels imposed on the EPBT are specified as the interval values $[EPBT_i^L, EPBT_i^U]$, thus reflecting distinct scenarios to be explored, the following interval constraint is obtained:

$$(7) \quad y_i EPBT_i \leq [EPBT_i^L, EPBT_i^U], \quad i = 1, \dots, n,$$

where y_i is a binary variable that allows identifying if lighting project 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).

Imposition of a maximum interval valued proportion of capital that can be invested. If we also consider the percentage of support assigned to each lighting project given in the interval range $[u_i^L, u_i^U]$, the following interval constraint is considered:

$$(8) \quad x_i \leq [u_i^L, u_i^U] y_i, \quad i = 1, \dots, n.$$

Therefore, from (5) to (8) the following multiobjective interval portfolio optimization model is obtained:

$$(9) \quad \begin{aligned} & \max \min \sum_{i=1}^n [r_{iT}^L, r_{iT}^U] x_i - \sum_{i=1}^n [r_i^L, r_i^U] x_i, \\ & \max \sum_{i=1}^n [SIR_i^L, SIR_i^U] x_i, \\ & \text{s. t: } \sum_{i=1}^n x_i = 1, \\ & \sum_{i=1}^n y_i \leq h, \\ & y_i EPBT_i \leq [EPBT_i^L, EPBT_i^U], \quad i = 1, \dots, n, \\ & x_i \leq [u_i^L, u_i^U] y_i, \quad i = 1, \dots, n, \\ & x_i \geq 0, \quad i = 1, \dots, n, \\ & y_i \in \{0, 1\}, \quad i = 1, \dots, n. \end{aligned}$$

Let $[\gamma^L, \gamma^U]$ 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 $[\gamma^L, \gamma^U] = \min \sum_{i=1}^n [r_{iT}^L, r_{iT}^U] x_i - \sum_{i=1}^n [r_i^L, r_i^U] x_i$. The risk function maximizes the minimum gain (i.e. minimizes de maximum loss) or alternatively it maximizes $[\gamma^L, \gamma^U]$, where $\sum_{i=1}^n [r_{iT}^L, r_{iT}^U] x_i - \sum_{i=1}^n [r_i^L, r_i^U] x_i \geq [\gamma^L, \gamma^U]$. This last equation guarantees that $[\gamma^L, \gamma^U]$ will be upper bounded by the minimum portfolio gain; because this is the only constraint on $[\gamma^L, \gamma^U]$ and since $[\gamma^L, \gamma^U]$ is being maximized, it will take on the value of the maximum minimum gain, or the minimum maximum loss. Then, problem (9) has the following surrogate multiobjective interval integer linear programming problem:

$$\begin{aligned} & \max [\gamma^L, \gamma^U], \\ & \max \sum_{i=1}^n [SIR_i^L, SIR_i^U] x_i, \\ & \text{s. t: } \sum_{i=1}^n x_i = 1, \\ & \sum_{i=1}^n y_i \leq h, \\ & y_i EPBT_i \leq [EPBT_i^L, EPBT_i^U], \quad i = 1, \dots, n, \\ & \sum_{i=1}^n [r_{iT}^L, r_{iT}^U] x_i - \sum_{i=1}^n [r_i^L, r_i^U] x_i \geq [\gamma^L, \gamma^U], \\ & x_i \leq [u_i^L, u_i^U] y_i, \quad i = 1, \dots, n, \end{aligned}$$

$$\begin{aligned}
x_i &\geq 0, i=1, \dots, n, \\
y_i &\in \{0,1\}, i=1, \dots, n, \\
\gamma^L, \gamma^U &\geq 0.
\end{aligned} \tag{10}$$

2.4 The solution approach

Problem (10) can be converted into a mixed integer linear optimization problem through the use of reference point-based techniques (Henriques et al., 2018). Finally, we consider distinct optimization models for portfolio selection regarding three types of investment strategies: conservative, aggressive and combined.

Conservative strategy

The public investor pursuing a conservative strategy is more risk averse, being more concerned with risk than return. Consequently, this type of investor seeks to maximize return and to minimize risk in the worst case scenario as follows:

$$\begin{aligned}
\min v &+ \rho \left((\gamma^{L*} - \gamma^L) + (SIR^{L*} - \sum_{i=1}^n SIR_i^L x_i) \right), \\
s. t: &\sum_{i=1}^n x_i = 1, \\
&\sum_{i=1}^n y_i \leq h, \\
&y_i EPBT_i \leq EPBT_i^L, i=1, \dots, n, \\
&\sum_{i=1}^n r_{iT}^L x_i - \sum_{i=1}^n r_i^U x_i \geq \gamma^L, \\
&(\gamma^{L*} - \gamma^L) \leq v, \\
&(SIR_i^{L*} - \sum_{j=1}^n SIR_j^L x_i) \leq v, i=1, \dots, n, \\
&x_i \leq u_i^L y_i, i=1, \dots, n, \\
&x_i \geq 0, i=1, \dots, n, \\
&y_i \in \{0,1\}, i=1, \dots, n, \\
&\gamma^L \geq 0. \\
v &\geq 0,
\end{aligned} \tag{11}$$

where $\rho > 0$ is a sufficiently small scalar, γ^{L*} and SIR^{L*} are the individual optimal values of the corresponding objective functions both considering the lower bounds of each objective function and the tightest version of the feasible region.

Aggressive strategy

The investor aiming for an aggressive strategy is more prone to risk, being more concerned with return than risk. In this case, the investor strives for the maximization of return and the minimization of risk in the best case scenario:

$$\begin{aligned}
\min v &+ \rho \left((\gamma^{U*} - \gamma^U) + (SIR^{U*} - \sum_{i=1}^n SIR_i^U x_i) \right), \\
s. t: &\sum_{i=1}^n x_i = 1, \\
&\sum_{i=1}^n y_i \leq h, \\
&y_i EPBT_i \leq EPBT_i^U, i=1, \dots, n, \\
&\sum_{i=1}^n r_{iT}^U x_i - \sum_{i=1}^n r_i^L x_i \geq \gamma^U, \\
&(\gamma^{U*} - \gamma^U) \leq v, \\
&(SIR_i^{U*} - \sum_{j=1}^n SIR_j^U x_i) \leq v, i=1, \dots, n, \\
&x_i \leq u_i^U y_i, i=1, \dots, n, \\
&x_i \geq 0, i=1, \dots, n, \\
&y_i \in \{0,1\}, i=1, \dots, n, \\
&\gamma^U \geq 0. \\
v &\geq 0,
\end{aligned} \tag{12}$$

where γ^{U*} and SIR_i^{U*} are the individual optimal values of the corresponding objective functions both considering the upper bounds of each objective function and the widest version of the feasible region.

Combined Strategy

A combined strategy allows for the investor to choose a more balanced approach regarding risk and return.

$$\begin{aligned}
\min v &+ \rho \left(\alpha (\gamma^{L*} - \gamma^L) + \beta (SIR^{L*} - \sum_{i=1}^n SIR_i^L x_i) + (1 - \alpha) (\gamma^{U*} - \gamma^U) + (1 - \beta) (SIR^{U*} - \sum_{i=1}^n SIR_i^U x_i) \right), \\
s. t: &\sum_{i=1}^n x_i = 1, \\
&\sum_{i=1}^n y_i \leq h, \\
&y_i EPBT_i \leq EPBT_i^U - \varphi_i (EPBT_i^U - EPBT_i^L), i=1, \dots, n,
\end{aligned}$$

$$\begin{aligned}
& (\sum_{i=1}^n r_{IT}^U x_i - \sum_{i=1}^n r_i^L x_i) + (\alpha) (\sum_{i=1}^n r_{IT}^L x_i - \sum_{i=1}^n r_i^U x_i) - (\sum_{i=1}^n r_{IT}^U x_i - \sum_{i=1}^n r_i^L x_i) \geq (\gamma^U + (\alpha)(\gamma^L - \gamma^U)), \\
& (\sum_{i=1}^n r_{IT}^U x_i - \sum_{i=1}^n r_i^L x_i) + (1 - \alpha) (\sum_{i=1}^n r_{IT}^L x_i - \sum_{i=1}^n r_i^U x_i) - (\sum_{i=1}^n r_{IT}^U x_i - \sum_{i=1}^n r_i^L x_i) \geq (\gamma^U + (1 - \alpha)(\gamma^L - \gamma^U)), \\
& \alpha (\gamma^{L*} - \gamma^L) + (1 - \alpha) (\gamma^{U*} - \gamma^U) \leq v, \\
& \beta (SIR_i^{L*} - \sum_{j=1}^n SIR_j^L x_i) + (1 - \beta) (SIR_i^{U*} - \sum_{j=1}^n SIR_j^U x_i) \leq v, i=1, \dots, n, \\
& x_i \leq (u_i^U - \delta_i(u_i^U - u_i^L))y_i, i=1, \dots, n, \\
& x_i \geq 0, i=1, \dots, n, \\
& y_i \in \{0,1\}, i=1, \dots, n, \\
& \gamma^L, \gamma^U \geq 0. \\
& v \geq 0,
\end{aligned} \tag{13}$$

where α and β reflect the importance of reaching the reference targets for each objective function, while φ_i and δ_i are indexes of pessimism ranging on a scale from zero to one.

3 Data

The national IO tables and the corresponding satellite accounts, specifically regarding energy consumption, were obtained from the world IO database¹ (Timmer et al., 2012). Furthermore, the Portuguese Consumption Efficiency Promotion Plan - PPEC - 2013-2014 and PPEC - 2017-2018 (<http://www.erse.pt/>) allowed us to gather information regarding the number of operating days, the lifespan, the cost (with the assumption of a 25% margin of profit) and the type of lighting projects that were used as a starting point in our analysis - see Table 1. The computation of the average portion of materials and costs being assigned to each lighting project under assessment were derived from Welz et al. (2011) and Soneji (2008). The percentage of imported material was calculated according to data available from the IO table - see Table 2. The information regarding the electricity production mix (in 2013) and the corresponding costs of generation were based on Rocha (2012). The base year of our study was 2013, in order to guarantee the consistency of data available from the different sources of information.

Table 1. Specific characteristics of the lighting projects under evaluation.

<i>Code</i>	<i>Business as usual (BAU) lighting systems</i>	<i>Best available technology (BAT) lighting systems</i>	<i>Lifespan (Years)</i>	<i>Annual energy savings (kWh)</i>
L1	T8	T5 luminaires	16	142
L2	TFL and others	LED luminaires	6	528
L3	HPS	T5 luminaires + Light control system	16	447
L4	T8	T5 luminaires	16	239
L5	T8 and HPS	T5 and LED lamps	12	244
L6	T8	LED luminaires	6	430
L7	T8 and Halogen	LED lamps	6	116
L8	T8 and HPS	LED luminaires	6	406
L9	-	Light control system	15	27,375

Note: TFL – Tubular fluorescent lamps; HPS – High pressure steam lamps; LED – Lighting emitting diode

Table 1. Share of materials, costs and imports.

		<i>L1</i>	<i>L2</i>	<i>L3</i>	<i>L4</i>	<i>L5</i>	<i>L6</i>	<i>L7</i>	<i>L8</i>	<i>L9</i>
Share of material	Glass	20.4%	14.5%	20.4%	20.4%	18.1%	14.5%	14.5%	14.5%	0.0%
	Metal	42.5%	40.3%	42.5%	42.5%	41.3%	40.3%	40.3%	40.3%	0.0%
	Plastic	6.2%	23.4%	6.2%	6.2%	12.3%	23.4%	23.4%	23.4%	0.0%
	Electronic	30.7%	21.8%	30.7%	30.7%	27.2%	21.8%	21.8%	21.8%	100%
Share of cost	Glass	2.0%	1.7%	2.0%	2.0%	1.9%	1.7%	1.7%	1.7%	0.0%
	Metal	49.1%	55.4%	40.0%	40.0%	50.9%	55.4%	55.4%	55.4%	0.0%
	Plastic	0.5%	2.1%	0.5%	0.5%	1.0%	2.1%	2.1%	2.1%	0.0%
	Electronic	48.4%	40.8%	58.0%	58.0%	45.2%	40.8%	40.8%	40.8%	100%
Share of imports	Glass	18.8%	18.8%	18.8%	18.8%	18.8%	18.8%	18.8%	18.8%	0.0%
	Metal	54.2%	54.2%	54.2%	54.2%	54.2%	54.2%	54.2%	54.2%	0.0%
	Plastic	51.5%	51.5%	51.5%	51.5%	51.5%	51.5%	51.5%	51.5%	0.0%
	Electronic	39.5%	39.5%	39.5%	39.5%	39.5%	39.5%	39.5%	39.5%	100%

¹ Available at: <http://www.wiod.org/>

Figures 1 and 2 depict information regarding the values computed both for the EPBT and the SIR for each lighting project, respectively. This later indicator was computed by assuming a discount rate of 2% to 5% and a subsidisation level of 65% to 80% of the estimated investment cost (following the usual assumptions adopted in this sort of programmes). Finally, the maximum percentage of investment in each lighting project is assumed to go from 25% to 60%, imposing a certain diversification level; while the upper interval bound on the EPBT is assumed to lie between the average value obtained for this indicator among all technologies considered (1.3 months) and the highest EPBT attained (2.22 months) – see Figure 1.

The replacement of T8 luminaires with T5 luminaires leads to the highest overall EPBT, while the adoption of a light control system has the lowest EPBT. In this last case, this is the result of the assumption that the electronic components incorporated in these technologies are fully imported. The fact that the replacement of BAU with BAT lighting technologies always leads to higher indirect energy embodied than direct energy embodied, highlights the importance of following the EIO-LCA approach in the assessment of the energy performance of these lighting technologies.

Finally, the highest SIR is obtained with the replacement of T8 luminaires and HPS with T5 and LED lamps, whereas the replacement of T8 and HPS with LED luminaires represents to the lowest SIR.

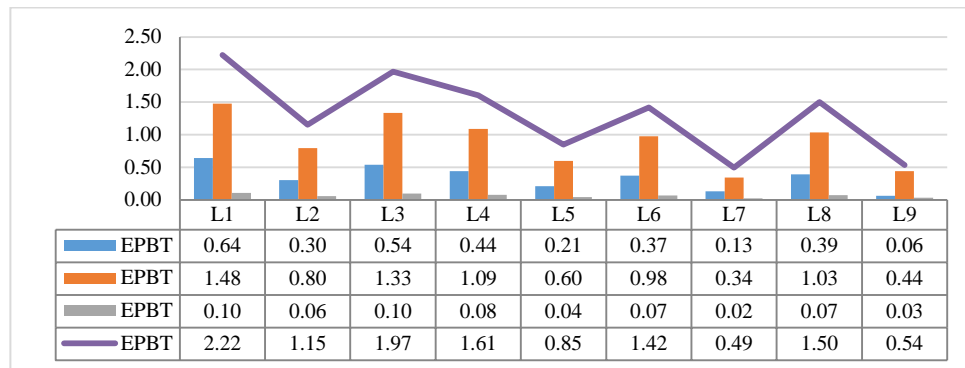


Figure 1. EPBT in months per each lighting technology.

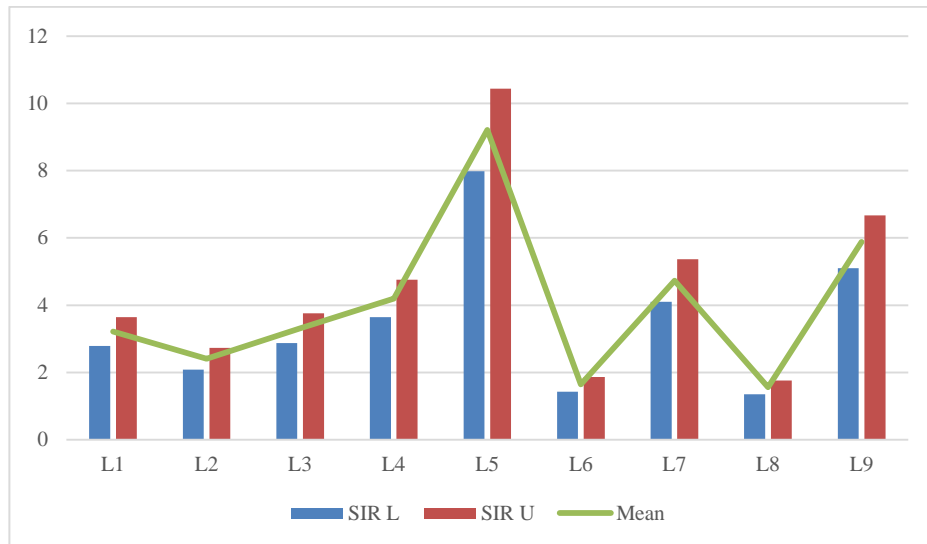


Figure 2. SIR per each lighting technology.

4 Results

The upper and lower possible values calculated for return (SIR) and risk (maximization of the minimum deviation of the energy savings from the energy incorporated in the portfolio) regarding each solution obtained, considering that all indices of pessimism vary equally and simultaneously, are illustrated in Figure 3. The information related to the composition of the possibly efficient portfolios selected is given in Table 3. Solutions 1 and 2 correspond to the individual optimal values of risk and return according to a worst case scenario (i.e. considering the lower bounds of the objective functions and the tightest version of the feasible region, thus following a conservative stand point) and Solutions 3 to 4 allow obtaining the individual optimal values of these objective functions assuming a best case scenario (i.e. considering the upper bounds of the objective functions and the widest version of the feasible region, thus assuming an aggressive stance). Solutions 5 to 11 deem combined strategies, that go from highly conservative to highly aggressive strategies.

The compromises among risk and return of Solutions 1 to 11 are shown in Figure 3, indicating that portfolios leading to higher risk involve higher return and vice-versa. These outcomes corroborate the investor's stand point,

since the adoption of more aggressive strategies towards return usually result in higher risk and return while the opposite takes place with the adoption of more conservative strategies towards return.

Under a conservative strategy, i.e. with $\varphi_i = \delta_i = 1$ for all $i = 1, \dots, 9$, the same EE lighting portfolios are obtained either with the optimization of risk or return. In this case the higher level of diversification is attained with the even assignment of support (25%) among the following options: 1) replacement of TFL and other lamps with LED luminaires – L2; 2) replacement of T8 and HPS lamps with T5 and LED lamps – L5; 3) replacement of T8 and Halogen lamps with LED lamps – L7; 4) promote the adoption of light control systems – L9.

If the DM considers a highly aggressive strategy, i.e. with $\varphi_i = \delta_i = 0$ for all $i = 1, \dots, 9$, the lowest level of diversification is reached with only two technologies selected in terms of support. In this situation, the majority of investment (60%) should be channelled to the replacement of T8 and HPS lamps with T5 and LED lamps (L5), while the remaining investment should foster the adoption of light control systems (L9). It is interesting to see that these two investment options are always contemplated in the efficient portfolios obtained irrespective of the strategy followed. In the first case, these results are sustained by the fact that option L5 has the highest SIR, while it has the second lowest EPBT of the sample of technologies herein analysed, whereas with option L9, the second highest SIR and the lowest EPBT are obtained.

The following replacement options are never selected regardless of the strategy followed: T8 with T5 luminaires – L1; HPS with T5 luminaires using light control systems – L3; T8 with LED luminaires – L6; T8 and HPS with LED luminaires – L8. These outcomes are related to the fact that these options lead to an EPBT above average also presenting a return below average when contrasted to the other technologies.

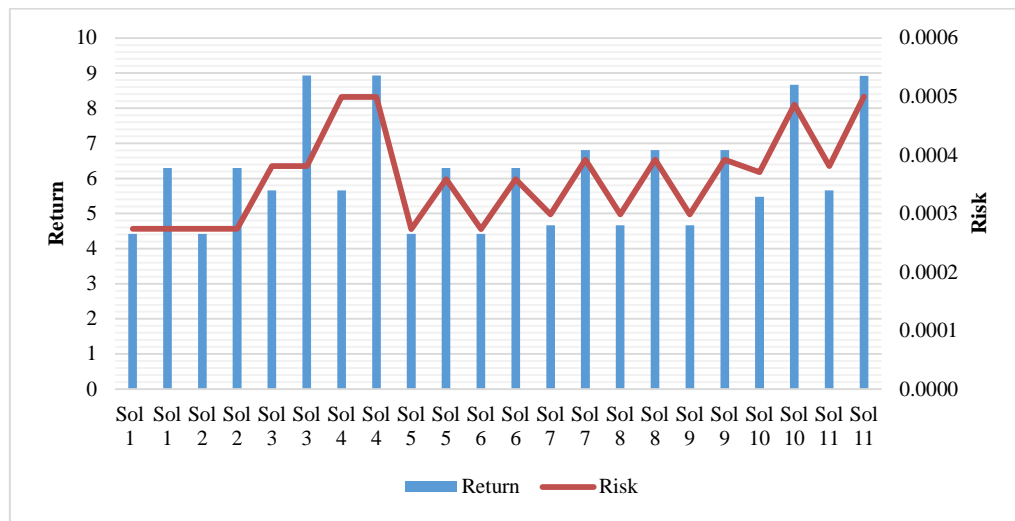


Figure 3. Return and risk obtained in each portfolio.

A different set of solutions has also been computed, assuming that the DM wants to guarantee the highest diversification level of the lighting technologies to be funded (i.e. the promotion of four distinct technologies) under different settings, i.e. $\varphi_i = 1$ for all $i = 1, \dots, 9$. Figure 4 depicts the increase of risk and SIR, that is consistent with the increase of aggressiveness of the strategies pursued, while Table 4 reveals information concerning the EE lighting technologies selected accordingly (Solutions 12 to 17). In this case, the allocations of investment are always evenly distributed among the four technologies selected in each portfolio. It might be concluded that option L2 (i.e. the replacement of TFL and other lamps with LED luminaires) is only appealing from a conservative point of view, while option L4, which corresponds to the replacement of T8 with T5 luminaires, becomes an interesting alternative to be supported in the remaining cases (according to Solutions 13 to 17). It can also be established that options L5 and L9 have the highest preference in terms of support, irrespective of the strategy adopted.

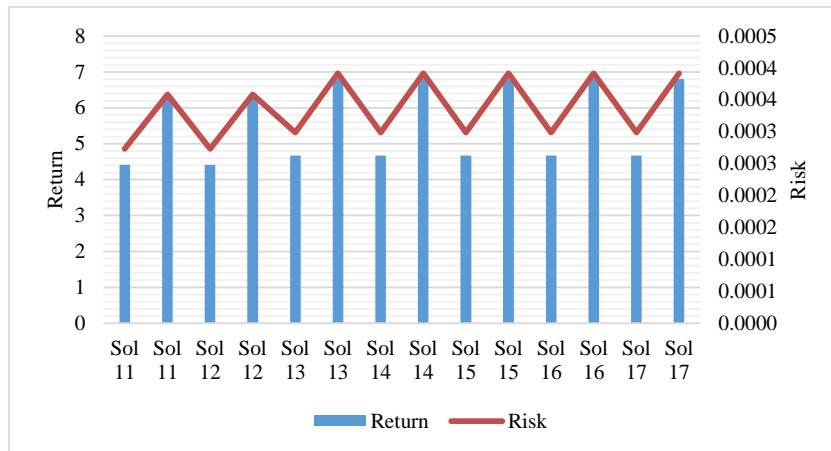


Figure 4. Return and risk obtained in each portfolio (considering the highest diversification level possible).

Finally, it is worth mentioning that the substitution of T8 and Halogen lamps with LED lamps – L8 (which is never selected with the modelling framework developed in any of the scenarios herein reviewed) has been effectively elected for public support in order to foster the investment in EE lighting projects in the industrial sector (the dark shaded rows in Tables 3 and 4 correspond to the technologies selected for public funding). This outcome might be explained by the fact that financial reasons are the main driver underlying the selection of the technologies to be fostered/supported by public bodies in investment planning for energy efficiency programs. These results highlight the importance of using other approaches which explicitly account for the energy/environmental performance of the technologies from a life-cycle perspective.

Our findings suggest that LED lamps (LED luminaires according to a conservative stand point) and T5 technologies are valuable investment options for the replacement of T8 and HPS lighting systems. Lastly, despite the high investment costs of light control systems they allow reaching a reduced EPBT and a high SIR, respectively.

5 Summary and Conclusions

This paper presents a novel methodological framework that can be used to support public bodies in investment planning for energy efficiency programs. This methodology combines portfolio theory with the EIO-LCA approach. In a first step, the specification of the systems' boundaries has been established, being subsequently intertwined with the EIO-LCA methodology, enabling the computation of the direct, indirect and induced energy incorporated across the life-cycle stages considered for the assessment of the efficient lighting projects under scrutiny. Subsequently, a new methodology for computing the EPBT for assessing the energy performance of the EE lighting projects under analysis has been used by considering the EIO-LCA approach. One of the main advantages of adopting this methodology is that it can be easily adjusted to encompass the appraisal of other environmental impacts (e.g. the greenhouse gas payback time, among others).

Additionally, contrarily to traditional portfolio models where the coefficients are usually viewed as deterministic, the coefficients of the objective functions and of the constraints of the multiobjective portfolio model suggested are given as intervals, enabling the exploration of distinct scenarios.

New measures of return and risk have also been used as proxies which are accustomed to the appraisal of EE technologies, in particular the SIR and the maximization of the minimum deviation of energy savings of the portfolio from the energy incorporated in its manufacture and installation, respectively.

Besides capital budget constraints typically found in traditional portfolio problems, cardinality constraints regarding the number of technologies considered for funding have also been used, thus imposing a certain diversification level of the portfolios selected. Constraints have also been considered regarding both the maximum amount of money allocated to each EE lighting project and the acceptable EPBT.

The solution approach herein suggested to compute the possibly efficient portfolios to be selected is based on reference point techniques and allows accounting for the preferences of the public DM, ranging from the adoption of more aggressive to less aggressive investment strategies. Contrastingly to the methodology used in Henriques and Coelho (2017) (which might disregard unsupported non-dominated solutions) this solution procedure guarantees the computation of both supported and unsupported efficient solutions.

Generally, the results obtained suggest that LED lamps and T5 technologies are valuable investments for replacing T8 and HPS technologies in the industrial sector. Additionally, fostering the use of light control systems seems to be a proficuous option, in spite of the investment initially required. Furthermore, it might be stated that, with the necessary modifications, this modelling framework can be easily adjusted (if the required data are available) to help shape other energy policy measures aimed at promoting the investment in other EE equipment.

Finally, we acknowledge that there are still areas that require further improvements because of the scarcity of data available, in particular addressing the material cost shares of each technology and the disposal of lighting systems. Therefore, in the future, additional efforts should contemplate other possible hybrid IO LCA frameworks aimed at mitigating these limitations.

Table 3. Investment assignment per lighting technology.

	Max min Risk	Max SIR	Max min Risk	Max SIR	Combined	Combined	Combined	Combined	Combined	Combined	Combined
Strategy	Conservative $\varphi_i = \delta_i = 1$ for all $i = 1, \dots, 9.$	Conservative $\varphi_i = \delta_i = 1$ for all $i = 1, \dots, 9.$	Aggressive $\varphi_i = \delta_i = 0$ for all $i = 1, \dots, 9.$	Aggressive $\varphi_i = \delta_i = 0$ for all $i = 1, \dots, 9.$	Highly conservative $\alpha = \beta = \varphi_i = \delta_i = 1$ for all $i = 1, \dots, 9.$	Strongly conservative $\alpha = \beta = \varphi_i = \delta_i = 0.7$ for all $i = 1, \dots, 9.$	Moderately conservative $\alpha = \beta = \varphi_i = \delta_i = 0.6$ for all $i = 1, \dots, 9.$	Intermediate $\alpha = \beta = \varphi_i = \delta_i = 0.5$ for all $i = 1, \dots, 9.$	Moderately aggressive $\alpha = \beta = \varphi_i = \delta_i = 0.4$ for all $i = 1, \dots, 9.$	Strongly aggressive $\alpha = \beta = \varphi_i = \delta_i = 0.2$ for all $i = 1, \dots, 9.$	Highly aggressive $\alpha = \beta = \varphi_i = \delta_i = 0$ for all $i = 1, \dots, 9.$
Solution	Solution 1	Solution 2	Solution 3	Solution 4	Solution 5	Solution 5	Solution 6	Solution 7	Solution 8	Solution 9	Solution 9
L1	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
L2	25%	25%	0%	0%	25%	25%	0%	0%	0%	0%	0%
L3	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
L4	0%	0%	0%	0%	0%	0%	25%	25%	25%	0%	0%
L5	25%	25%	60%	60%	25%	25%	25%	25%	25%	53%	60%
L6	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
L7	25%	25%	0%	0%	25%	25%	25%	25%	25%	0%	0%
L8	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
L9	25%	25%	40%	40%	25%	25%	25%	25%	25%	47%	40%

Acknowledgements

This work was partially supported by the European Regional Development Fund in the framework of COMPETE 2020 Programme through project UID/MULTI/00308/2019, the FCT Portuguese Foundation for Science and Technology within project T4ENERTEC (POCI-01-0145-FEDER-029820) and the European Regional Development Fund and Programa Operacional Regional do Centro e do Programa Operacional Regional de Lisboa through project n.º 023651, Learn2Behave (IIA - 02/SAICT/2016).

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