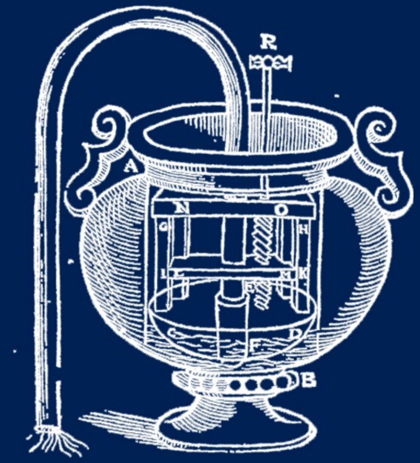
CNR-IRCrES Working Paper

The proposal of a new hybrid methodology for the impact assessment of energy efficiency interventions

An exploratory study



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The proposal of a new hybrid methodology for the impact assessment of energy efficiency interventions
An exploratory study

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ABSTRACT
The paper proposes a preliminary analysis of a combination of two very interesting techniques used for assessing the economic and environmental sustainability of retrofitting interventions in the building sector and their eco-efficiency.

Indeed, one of the most popular methodologies proposed by the literature is the Life Cycle Assessment (i.e., LCA) because it considers not only costs and investment necessary for an intervention but also its spillovers on environment and society. For this reason, the LCA can be considered a technique able to guarantee a holistic assessment of retrofitting. However, data required for LCA are not always so easy to find and the necessity to evaluate the holistic impact of the intervention remains unsolved.

This paper suggests a hybrid methodology for evaluating different solutions of retrofitting interventions combining results from Life Cycle Costing (LCC) with those from the non-parametric technique of the Directional Distance Function (DDF).

The simplicity but, at the same time, the completeness of these methodologies allow to obtain efficient scores that can help to evaluate the holistic impact of retrofitting interventions on buildings, in particular in terms of energy savings and less CO2 emissions in the environment.

KEYWORDS: life cycle cost, directional distance function, retrofitting, building sector.

JEL CODES: F64; L74; P25

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CONTENTS

1. INTRODUCTION

The issues of environmental protection and sustainability in industrial activities has been even more studied all over the world and in Europe. The focus is mostly on the green performance of production processes both in term of emissions and energy savings. More recently, a strong attention to all process with an impact on environment or on society is increasing.

In this context, the scientific research works in order to define performance measures able to consider both environmental and social impact. The missing availability of information on the costs, the typologies, and amounts of pollution stimulates researchers to study new techniques, both non-parametric and parametric, dealing with this issue. Starting from contribution by Färe et al. (1989) suggesting a hyperbolic efficiency measure with non-linear constraints to standard Data Envelopment (DEA) methodology, numerous applications have been studied. Zhou et al. (2008a) studies about 100 environmental applications using DEA linear programming, while Scheel (2001) analyses strengths and weaknesses of main models. A part of the literature on efficiency introduces undesirable outputs using stochastic frontier (Zofio & Prieto, 2001; Ball et al., 2004; Cuesta & Zofio, 2005), while the asymmetric treatment of good and bad is more difficult where non-parametric models are applied. Chambers et al. (1996) and Chambers et al. (1998) study the Directional Distance Function (DDF) as a model able to modify the direction in which searching for the efficient counterpart of each observation, without changing the definition of technology. Another insight of the DDF is the additivity, which makes it possible to adopt a standard linear programming procedure, without assumptions about the functional form of technology.

A first set of applied researches refers to US micro-data on very specific sectors such as paper and pulp mills (Chung et al., 1997), glass plants (Boyd et al., 2002), public transport firms (McMullen & Noh, 2007), thermal power plants (Färe et al., 2007; Kumar & Managi, 2010a). A second stream of studies applies non-parametric models on regional data (Macpherson et al., 2010), world countries (Kumar & Managi, 2010b), Chinese provinces (Zang et al., 2011), Italian provinces (Falavigna et al., 2013) or UK regions (Halkos & Tzeremes, 2013).

Finally, a more recent stream of literature suggests to combine non-parametric technique to well-known Life-Cycle Cost (LCC) or Life-Cycle Assessment (Lozano et al., 2009; Álvarez-Rodríguez et al., 2019; Pishgar-Komleh et al., 2020) in order to evaluate the sustainability of an industry sector (Ibáñez-Forés, 2014) or, more in general, of an intervention. In this specific case, authors refer to the action of renovating a part of the production process, buying new machineries or implementing good practices aimed at improving the sustainability of production. Anyway, literature suggests that LCA is a useful approach for estimating in a quite simple way the return of an investment. In present work, the intervention studied refers to the retrofitting a building that involves changing its systems or structure after its initial construction and occupation. This work can improve amenities for the building's occupants and improve the performance of the building. As technology develops, building retrofits can significantly reduce energy and water usage.

Considering the LCA, necessary data are not always available, then in the present study we propose to combine the LCC estimation with a specification of the standard DEA model, able to consider undesirable outputs, as, for instance, CO_2 emissions. In addition, a bootstrap procedure has been adopted in order to obtain more robust results, as suggested in recent studies (Yang et al., 2020).

The present work proposes a quite innovative approach. Other studies suggest the combination of LCA and Data Envelopment Analysis for the evaluation of mussel cultivation (Lozano et al., 2009). The same framework is suggested by Iribarren et al. (2010) that studied the environmental efficiency of Galician farms.

Other hybrid methodologies have been successfully applied as for instance by Kjær et al. (2015) where authors suggest a joint use of LCC and environmental input-output LCA in the maritime sector. Results suggest how the combination of the two techniques can be a real useful tool for decision making.

The aim of the paper is to elaborate preliminary data collected by the European project CSA HAPPEN[1] with the aim to define a hybrid model, based on LCC estimates and Directional Distance Function for the impact assessment of energy efficiency interventions in the building sector. The results of the proposed approach should suggest which retrofitting interventions are the most efficient under a holistic point of view, considering also the environmental impact (in terms of CO_2 emissions and Energy Savings) of the proposed retrofitting solutions. The paper in fact originates from a complex European project in which various retrofitting case studies are analyzed in different countries and in different climatic zones. The main output of these case studies is a database that contains, for each case analyzed, the combinations of the best retrofitting solutions that can be adopted (so-called PoS, or Packages of solutions) in those specific climatic conditions to obtain the best energy savings. The validity of each PoS is measured according to some variables, including above all the achievable energy savings and the consequent CO_2 emissions savings. As our paper is based on the data made available by the project, the choice of using the variable of CO_2 emissions was agreed with the partners; furthermore, as CO_2 can be considered the main factor in influencing the global warming and climate change, this already justifies its choice as a variable to be used in our model.

The paper is organized as follows: materials and methods are presented in section 2, the empirical results are presented in section 3; whereas conclusions and discussion are proposed in section 4.

2. MATERIALS AND METHODS

2.1. Methodology: biased directional distance function

The Directional Distance Function is a non-parametric technique widely used in the environmental field in order to evaluate the efficiency of production process of firms considering also emissions.

The difference of this technique compared with other non-parametric models is the possibility to consider different type of outputs. Indeed, standard data envelopment analysis (DEA) considers efficient that observation is able either to maximize outputs taking equal inputs (output-oriented); or to produce the same output minimizing necessary inputs (input-oriented). However, the standard hypothesis is that the output is a good production. The literature proposing the efficiency models aims at evaluating the ability of firm to produce using the minimum level of resources. The production process of firms is also defined technology and it represents how firm organizes the production factors. In this context, some extensions of DEA methodology have been proposed in order to define models representing different concept of efficiency.

The Directional Distance Function (DDF) is a generalization of the DEA model and allows to consider the dual nature of output following Cooper et al. (2007). For this purpose, it has been

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[1] The Holistic APproach and Platform for the deep renovation of the Med residential built Environment (HAPPEN) is an EU Coordination and Support Action involving 13 partners from 7 Mediterranean Countries; it pursues the development and activation of a holistic and adaptive approach to deep and beyond retrofitting of existing buildings, in order to achieve a greater energy efficiency. Mediterranean specific characteristics are the cornerstone of the project strategy; therefore, social, financial, technical, legal and environmental aspects are taken into account to develop a holistic retrofitting MedZEB approach easily adaptable to all Mediterranean countries. The project's outputs are tested and validated in nine pilot sites in: Spain, France, Italy, Slovenia, Croatia, Greece and Cyprus.

necessary a redefinition of the model in order to take into consideration not only desirable and but also undesirable (or bad) outputs.

In detail, let the initial vector of $i = 1,2,\ldots,s$ outputs $\mathbf{y} \in \Re_{++}^{s}$, it is divided into good and undesirable output, i.e., $\mathbf{y} = (\mathbf{y}^d, \mathbf{y}^u)$ with $\mathbf{y}^d \in \Re_{++}^{g}$ and $\mathbf{y}^u \in \Re_{++}^{r}$. The technology is built considering constant returns to scale (CRS) and it is defined as $P_{CRS} = \left\{ \left(\mathbf{x}, \mathbf{y}^d, \mathbf{y}^u\right) | \, \mathbf{x} \geq X\lambda, \mathbf{y}^d \leq Y\lambda, \mathbf{y}^u = Y\lambda, \lambda \geq \mathbf{0} \right\}$. Literature is still working on variable returns to scale and the debate is not concluded yet. Until now, the majority of studies with directional distance function application considers constant return to scale (Mandal & Madheswaran, 2010; Zhou et al., 2008a; Zhou et al., 2008b; Riccardi et al., 2012; Färe et al., 1989; Falavigna & Ippoliti, 2019). In addition, in this specific application, the CRS assumption is reasonable because all package of solutions (POS) have been studied with the same criteria, suggesting that differences in the production do not depend from technology.

The DDF considers a pre-assigned direction that corresponds to the output vector, defined as $\mathbf{g}_y = \left(\mathbf{y}^d, \mathbf{y}^u\right) \neq \mathbf{0}_{m+s}$. Along this vector, it is possible to observe the projection of the efficiency measure $\left(\mathbf{x}_o, \mathbf{y}_o^d, \mathbf{y}_o^u\right)$ solving the following linear programming:

$$\max_{\beta,\lambda} \quad \beta$$

subject to:

$$\begin{aligned}
& X\lambda \leq \mathbf{x}_o \\
& Y^d\lambda \geq \mathbf{y}_o^d + \beta \mathbf{y}_o^d \\
& Y^u\lambda \geq \mathbf{y}_o^u - \beta \mathbf{y}_o^u \\
& \max\left\{\mathbf{y}_i^u\right\} \geq \mathbf{y}_o^u - \beta \mathbf{y}_o^u \\
& \lambda \geq \mathbf{0}
\end{aligned}$$

$\beta_{CRS}^{*} = 0$ represents the optimal solution (i.e., the observation is efficient); otherwise (i.e., $\beta_{CRS}^{*} > 0$), the observation is non-efficient.

As for standard DEA model, Färe et al. (2007) describe the axioms that the technology has to satisfy:

P1. $\{0\} \in P(x) \textit{ for all } x \in \Re_{+}^{N}$. This means that inactivity (i.e., production equal to 0) is always possible;

P2. $P(x) \textit{ is compact } x \in \Re_{+}^{N}$. This axiom highlights that finite inputs can only produce finite outputs;

P3. $P(x) \subseteq P(x') \textit{ if } x' \geq x$. This means that inputs are freely disposable. This property suggests that it is possible to increase or decrease inputs without constraints.

However, two additional axioms are required when DDF is applied. These properties are very important and they are respectively called weak disposability of outputs and null-jointness or byproduct:

P4(WD). $(y,b) \in P(x)$ and $0 \leq \theta \leq 1$ imply $(\theta y, \theta b) \in P(x)$. This axiom implies that a reduction of bad outputs requires a reduction in good outputs (Shephard, 1970).

P5(NJ). $(y,b) \in P(x)$ and $b = 0$ imply $y = 0$. This axiom means that bad outputs are byproducts of the good outputs. In other words, producing good outputs requires the production also of bad outputs.

As suggested by Simar and Wilson (1998; 2007) referring to the non-parametric models, bootstrapped scores perform well because the resampling methodology allows to obtain more robust efficiency estimates.

Bootstrapping concerns the replication of n dataset randomly starting from the initial sample and until now it has been applied only in few cases. For instance, in Falavigna et al. (2015), authors consider Italian judicial systems and they proposed a bootstrapped efficiency-productivity framework in order to improve the robustness of results. However, in general, bootstrapping is a mathematical procedure of re-sampling that can be applied to dataset with the aim to improve the quality of estimates. This procedure is recommended especially when the sample size is little because the replications of the methodology assure more robust estimates. The application of bootstrap to non-parametric technique has been introduced for the first time by Simar and Wilson (2007) which suggested to calculate a bias for correcting the efficiency scores and to be more confident on robustness of results (the so called "biased efficiency scores").

In this work, the procedure followed for the bootstrap computation is that suggested by Chernick (2008). Bootstrapping allows obtaining more robust results because it replies observations and model estimations guaranteeing a convergence of estimates. In literature, this methodology has been even more applied. Yang et al. (2020) have done a similar application of bootstrap to by-production (BP) technology for studying the eco-efficiency of 30 provinces of China from 2008 to 2017 concluding that bootstrapping non-parametric technique can improve the eco-efficiency estimations and the impact of pollutions.

Once having calculated the directional distance function scores for each bootstrapped sub-sample, each observation (called in DEA models Decision Making Units, DMUs) will present k efficiency scores (where 1 ≤ k ≤ size of sample * Number of replications).

Aiming at calculating the bias and the confidence intervals for efficiency scores, the Simar and Wilson (1998, 2007) procedure is followed.

In order to simplify the notation, considering the mathematical notation for i = 1, where i is the number of DMUs.

Let $\hat{\beta}^*(x,y)$ the efficiency score from the basic directional distance function model and $\hat{\beta}^b(x,y)$ the bootstrapped efficiency scores where b=1,…, B (replications).

The correction term for the efficiency score $\hat{\beta}^*(x,y)$ is found as the difference between the mean of bootstrapped efficiency scores ($\overline{\beta}^B(x,y)$) and the efficiency one:

$$bias = \frac{\sum_{b=1}^{B}\hat{\beta}^b(x,y)}{B} - \hat{\beta}^*(x,y) = \overline{\beta}^B(x,y) - \hat{\beta}^*(x,y)$$

The measure of efficiency with the correction of bias ($\hat{\beta}^*_B(x,y)$) is done by the difference between the efficiency score and the bias, that can be written as 2 times the efficiency score minus the mean of bootstrapped efficiency measure.

$$\hat{\beta}^*_B(x,y) = \hat{\beta}^*(x,y) \text{ -bias= } \hat{\beta}^*(x,y) - \frac{\sum_{b=1}^{B}\hat{\beta}^b(x,y)}{B} + \hat{\beta}^*(x,y) = 2\cdot\hat{\beta}^*(x,y) - \frac{\sum_{b=1}^{B}\hat{\beta}^b(x,y)}{B}$$

The standard error of the distribution of the corrected scores is calculated in the following manner:

$$s\hat{e} = \left\{\frac{1}{B-1}\sum_{b=1}^{B}\left[\hat{\beta}^b(x,y) - \overline{\beta}^B(x,y)\right]^2\right\}^{1/2}$$

Following Simar and Wilson (1998), the percentile confidence intervals (α=0.05) have to be calculated on the distribution of the bootstrapped efficiency scores subtracting 2 times the bias $\tilde{\beta}^b(x,y) = \hat{\beta}^b(x,y)$ -2*bias.

2.2. Data

Data for efficiency scores refer to preliminary results of Packages of Optimal Solutions (POS) for the deep retrofitting of the existing stock of buildings of 4 Mediterranean countries (pilot cases), defined in the project implementation.

16 POS starting from four pilot case studies have been proposed. Each POS proposes 12 solutions differing on the base of number and typology of retrofitting interventions (i.e., different renovation measures for the façades; measures for the renovation of the roofs, of the floors, of the thermal bridges, of the ventilation system, of the shading elements; different types of glazing). In addition, the case-studies have been selected considering 2 typologies of buildings (i.e., 2 single-family house, SFH and 2 multifamily houses, MFH) and 4 different climate zones (i.e., W1S2; W2S2; W2S3; W3S2).

Climate zones have been chosen in order to cover approximatively the whole Mediterranean area. The classification of the climate zones has been conducted on the base of the Climate Severity Index (CSI) that is a measure of climatic conditions and the W means winter (1 = less cold; 3 = colder), whereas S corresponds to summer (1= less hot; 3= hotter). The case-studies studied are the pilots from Croatia (HR) and Cyprus (CY) as SFH, whereas as MFH the front-runner pilots from France (FR) and Spain (SP) have been selected.

The following table (Table 1) summarizes the research strategy adopted for calculating efficiency scores. Indeed, 8 frontiers have been built, one for each typology of buildings and climate zone. For instance, considering the single-family house and the climate zone W1S2, 12 solutions from Cyprus and 12 solutions from Croatia have been considered simultaneously and then compared.

Table 1. Strategy design for efficiency score evaluation

Typology of building	Climate zones	Pilot studies	Pilot studies	Sample size (number of solutions)	DDF frontier
SFH	W1S2	CY (POS1)	HR (POS5)	24	1
	W2S2	CY (POS2)	HR (POS6)	24	2
	W2S3	CY (POS3)	HR (POS7)	24	3
	W3S2	CY (POS4)	HR (POS8)	24	4
MFH	W1S2	SP (POS13)	FR (POS9)	24	5
	W2S2	SP (POS14)	FR (POS10)	24	6
	W2S3	SP (POS15)	FR (POS11)	24	7
	W3S2	SP (POS16)	FR (POS12)	24	8

The sample size is not high but literature on non-parametric methodology suggests that, using constant return to scale, also a little sample allows obtaining acceptable results. In the seminal paper of Wilson (2018) an interesting debate on sample size is presented. The author suggests an algorithm based on the input-output space dimension of the model in order to identify the optimal dimension of the sample.

The input-output space for computing the DDF model has been built with the aim to evaluate which solution is the more efficient considering also CO_2 emissions. First of all, we decided to use the carbon dioxide because is one of the most relevant emission, as suggest by the European Commission (2015). However, in the building and energy fields it is still the most significant kind of emission compared to other sectors, such as e.g. that of the automotive industry, where for instance nitrogen dioxide (NO_2) or particulate (PM10) prevail. More in general CO_2, although it is not a dangerous emission for our health, influencing the increase of the planet's temperature with the greenhouse effect, has very significant consequences on the global warming and climate change with all their consequences.

With this intent, two input-output spaces have been considered. The outputs are equal for all formulation: one good output (i.e., the total final energy savings per year[2]) and one bad or undesirable (i.e., CO_2 emissions[3]). In the first model (i.e., model#1), the input is represented by the Life Cycle Costing (LCC) of solution; whereas in a second model (i.e., model#2) the total costs have been considered as input.

We decided comparing two different input-output spaces for estimating scores representing different meaning of eco-efficiency. In details, we proposed a standard input represented by the total costs of interventions and in this case, the model (i.e., model#2) assigns eco-efficiency scores considering the interventions more able to minimize CO_2 and maximize the final energy saving taking equal costs. Model#2 considers as input a more complete measure (i.e., Life Cycle Costing, LCC) that takes into consideration also the initial investment. This framework allows to obtain more convincing and effective scores because they consider all the production process of retrofitting interventions, both the saving of energy and the emissions of CO_2.

The Life Cycle Costing is a methodology that allows to evaluate costs throughout the entire life cycle of the product (i.e., retrofitting intervention), from production to the disposal phase. In the project, this variable has been calculated as the initial investment plus the operational costs in 30 years after implementing the optimal solutions. The total cost represents the total expense to implement the corresponding optimal solution.

However, moreover referring to model#2, the goal of the DDF is to compute a holistic efficiency score, able to compare different solutions considering together resources necessary for the retrofitting interventions and outputs for the whole society.

The meaning of DDF scores suggests which solution is the more efficient in maximizing the final energy saving and minimizing CO_2 emissions, taking equal the LCC (model#1) or the necessary total costs (model#2). Both the input-output space strategies are coherent with the axioms on DDF because CO_2 emissions are strictly linked to the activity of renovations. Indeed, retrofitting interventions involve changing systems and/or structure of a building and all these activities are made producing emissions. The basic idea of Directional Distance Function is that the so-called good output, in our case the energy saving, was produced together with the bad one, in our case CO_2 emissions. In other words, the axioms of DDF impose that it is not possible to have a recovery of energy without producing CO_2 emissions. In this way, the weak disposability and the null-jointness are verified. The combination of LCC and DDF allows obtaining holistic efficiency scores because they identify the total spillovers (i.e., positive and negative externalities) of the retrofitting interventions in terms of energy savings and CO_2 emissions. This hybrid approach can be considered as a different way for estimating the Life Cycle Assessment when some necessary data are missing. The scores are very simple to understand but, at the same time, their efficacy is proved in literature, always considering the difficulties due to data collection.

In both designs, the input-output space is made by 3 variables: 1 input and 2 outputs. Wilson (2018) suggests that the DEA model estimated under CRS, with an input-output space made by 3 variables and 24 observations (i.e., the size of samples) allows to obtain the same robustness of results that we would have expected with a linear regression run on a sample of 69 observations. In addition, the bootstrap and the following bias correction improve the quality of the estimates.

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[2] The total final energy savings per year (MWh) is the planned absolute value of the final energy savings per year.

[3] The CO2 emissions describe the value of the CO2 production after the implementation of the optimal solution proposed in the corresponding line.

Summarizing, we have defined two models, different in the input-output space. Each of these models has been run in order to obtain an efficiency frontier for each typology of building (i.e., SFH and MFH) and climate zone. This means that respectively 8 frontiers for model#1 and 8 for model#2 have been built.

Clearly, we have built 8 DDF frontier considering total costs and 8 with the LCC estimates. It seems necessary to underline again that different production technologies for each climate zone have been evaluated. Costs but especially the final energy consumptions can significantly change among geographical area. Table 2 shows descriptive statistics on all variables used as input-output space[4].

Table 2. Descriptive statistics of input-output space (mean values)

Typology of building	Input/ Output space	Variables	W1S2	W2S2	W2S3	W3S2
SFH	Input (#1)	LCC (mean value, €/m2)	143.10	178.47	219.18	234.50
	Input (#2)	Total costs (€)	18,158	20,006	21,457	22,336
	Bad output	CO2 emissions (kg/m2)	9.24	12.25	16.15	17.12
	Good output	Total final energy saving per year (MWh)	13.50	21.57	25.45	36.94
MFH	Input (#1)	LCC (mean value, €/m2)	115.64	155.71	189.20	199.21
	Input (#2)	Total costs (€)	32,258	46,631	49,920	51,519
	Bad output	CO2 emissions (kg/m2)	8.81	10.75	14.05	14.97
	Good output	Total final energy saving per year (MWh)	31.69	33.80	41.05	58.94

3. RESULTS: ECO-EFFICIENCY SCORES FOR SFH AND MFH

In present section, results obtained with DDF are presented. It is worth mentioning that, as explained in technical section, the more efficient solution presents a holistic efficiency score close to 0.

Results are shown based on typology of buildings and climate zone in order to identify the more efficient solutions within the group.

Considering the Single-Family House (SFH), case-studies analysed refer to Cyprus and Labin (Croatia).

Table 3 reports holistic efficiency scores computed on the 24 solutions of W1S2 climate zone.

The climate zone W1S2 is the less controversial case to analyse. Both models agree in suggesting the solution 9 as the most efficient. This is an interesting result because the first model can be interpreted as the holistic efficiency score, whereas Model#2 considers a technical evaluation: solution 9 is the best POS of climate zone W1S2. On the contrary, the solution less efficacy in terms of sustainability is the number 1, and this result is confirmed for each frontier.

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[4] Notice that different units of measure of variables is not a problem. Indeed, the linear programming is applied to each observation and then solutions are not optimized all together. For a deeper explanation of technical characteristics of non-parametric techniques see Farrell (1957).

Results concerning the climate zone W2S2 are less univocal. Model#1 highlights lower holistic efficiency score for the solutions 5 that is more performant also for Cyprus in model#2. Considering the case-study of Croatia, the best solution is the number 1.

Taking into account results for the third climate zone considered, Model#1 suggests that the more efficient holistic performance is obtained adopting solution number 9. The same result is confirmed by model#2 for Croatia. The situation for Cyprus suggests adopting solution 2.

Finally, referring to the last climate zone (W3S2), Model#1 suggests adopting solution 10 or 12 for Cyprus, and 2 for Croatia. Model#2 highlights solution 11 and 12 as more efficient for respectively Cyprus and Croatia.

Considering the Multi-Family House (MFH), two case studies of France and Spain have been evaluated and results are presented in Table 4.

In details, the front-runner pilots, placed in Marseille (France) and in Castellón (Spain). As for single-family houses, the same analysis has been carried on and 8 different frontiers have been built based on climate zones and input-output space.

In the climate zone W1S2 results are univocal and suggest, for both models, that holistic efficient frontier is the number 8 and it is interesting to notice that considering LCC as input, there are many optimal solutions in the case of France.

Results concerning the climate zone W2S2 are not concordant. Indeed, in this case, each model highlights a different efficient solution suggesting a greater variability of the climate zone.

Similar consideration refers to the climate zone W2S3 where for France, model#1 and model#2 agree on solution 7 as the most efficient, but for Spain, results change considering a different strategy of input-output space.

For the last climate zone, model#2 suggests for both case-studies that the efficient solution is the number 6; on the contrary, model#1 does not agree in highlighting a univocal efficient solution but it suggests to adopt different solutions in the analysed Countries.

Table 3. Holistic efficiency and technical-economic scores for SFH and all climate zone. (CY = Cyprus and HR = Croatia)

SOL.	W1S2				W2S2				W2S3				W3S2			
	MODEL#1		MODEL#2		MODEL#1		MODEL#2		MODEL#1		MODEL#2		MODEL#1		MODEL#2	
	CY POS1	HR POS5	CY POS1	HR POS5	CY POS2	HR POS6	CY POS2	HR POS6	CY POS3	HR POS7	CY POS3	HR POS7	CY POS4	HR POS8	CY POS4	HR POS8
1	0.032	0.160	0.198	0.140	0.023	0.121	0.031	0.014	0.017	0.032	0.045	0.040	0.090	0.320	0.076	0.285
2	0.022	0.159	0.160	0.102	0.036	0.149	0.121	0.095	0.018	0.119	0.024	0.022	0.073	0.305	0.257	0.330
3	0.021	0.155	0.143	0.120	0.024	0.144	0.113	0.081	0.003	0.118	0.134	0.024	0.045	0.307	0.093	0.290
4	0.019	0.155	0.148	0.100	0.033	0.116	0.165	0.083	0.005	0.084	0.153	0.017	0.036	0.306	0.000	0.353
5	0.014	0.157	0.128	0.086	0.001	0.102	0.014	0.192	0.005	0.118	0.061	0.085	0.042	0.310	0.069	0.334
6	0.010	0.155	0.113	0.085	0.005	0.191	0.037	0.135	0.006	0.184	0.058	0.067	0.005	0.379	0.263	0.368
7	0.000	0.114	0.177	0.037	0.009	0.174	0.040	0.056	0.016	0.138	0.149	0.081	0.039	0.323	0.093	0.422
8	0.007	0.121	0.117	0.009	0.003	0.194	0.021	0.027	0.014	0.162	0.235	0.117	0.005	0.345	0.215	0.428
9	0.000	0.000	0.101	0.000	0.006	0.261	0.087	0.130	0.000	0.000	0.050	0.000	0.003	0.425	0.070	0.396
10	0.000	0.101	0.140	0.039	0.013	0.190	0.097	0.032	0.003	0.133	0.160	0.136	0.000	0.326	0.131	0.409
11	0.003	0.110	0.124	0.024	0.001	0.171	0.089	0.098	0.001	0.140	0.064	0.129	0.001	0.307	0.015	0.422
12	0.000	0.117	0.128	0.010	0.000	0.104	0.140	0.310	0.000	0.136	0.227	0.092	0.000	0.323	0.029	0.261

Table 4. Holistic efficiency and technical-economic scores for MFH and all climate zone. (FR = France and SP = Spain)

SOL.	**W1S2**				**W2S2**				**W2S3**				**W3S2**			
	MODEL#1		**MODEL#2**		**MODEL#1**		**MODEL#2**		**MODEL#1**		**MODEL#2**		**MODEL#1**		**MODEL#2**	
	FR POS9	**SP POS13**	**FR POS9**	**SP POS13**	**FR POS10**	**SP POS14**	**FR POS10**	**SP POS14**	**FR POS11**	**SP POS15**	**FR POS11**	**SP POS15**	**FR POS12**	**SP POS16**	**FR POS12**	**SP POS16**
1	0.022	0.242	0.069	0.376	0.013	0.004	0.413	0.776	0.053	0.007	0.552	0.132	0.026	0.068	0.582	0.048
2	0.020	0.151	0.151	0.211	0.022	0.253	0.322	0.143	0.064	0.087	0.498	0.056	0.045	0.051	0.549	0.160
3	0.015	0.132	0.032	0.174	0.018	0.274	0.403	0.197	0.043	0.140	0.535	0.097	0.038	0.029	0.645	0.022
4	0.005	0.122	0.087	0.150	0.018	0.169	0.357	0.062	0.056	0.083	0.511	0.818	0.059	0.024	0.643	0.040
5	0.000	0.089	0.187	0.125	0.009	0.060	0.232	0.243	0.018	0.143	0.305	0.058	0.021	0.063	0.369	0.064
6	0.011	0.074	0.046	0.064	0.004	0.238	0.370	0.012	0.009	0.114	0.455	0.023	0.009	0.041	0.038	0.038
7	0.000	0.045	0.043	0.029	0.017	0.068	0.483	0.277	0.000	0.094	0.033	0.047	0.035	0.048	0.615	0.092
8	0.000	0.000	0.000	0.000	0.021	0.294	0.509	0.000	0.023	0.136	0.505	0.000	0.015	0.077	0.467	0.195
9	0.000	0.095	0.008	0.074	0.000	0.158	0.351	0.086	0.000	0.072	0.445	0.055	0.045	0.020	0.662	0.089
10	0.000	0.060	0.062	0.028	0.000	0.036	0.322	0.301	0.006	0.092	0.410	0.074	0.060	0.032	0.660	0.132
11	0.004	0.141	0.009	0.095	0.011	0.081	0.461	0.078	0.021	0.019	0.507	0.049	0.002	0.123	0.236	0.938
12	0.005	0.132	0.115	0.076	0.004	0.107	0.367	0.059	0.029	0.113	0.445	0.001	0.021	0.075	0.522	0.059

4. CONCLUSION AND DISCUSSION

The present paper has the aim to propose a hybrid methodology for assessing the retrofitting investments identified and analyzed in the European project HAPPEN. Results shown in this manuscript are preliminary and data collected have been used for testing and validating the innovative hybrid methodology.

Previous section presents the output of Directional Distance Function model where, as input, in Model#1 has been introduced the Life Cycle Cost and in Model#2 the total costs of the intervention. As presented the two models suggest different results and this confirms that obtained scores represent different meaning of efficiency. Standard concept of efficiency score refers to Model#2, where outputs represent which intervention produces less CO_2 and more final energy saving, taking equal costs. This result can be considered as the standard eco-efficiency measure, as suggested by literature and considering the sample size. However, even if these eco-efficiency scores are useful and in line with current literature, they do not consider the initial investment necessary for the retrofitting intervention and all sustained costs during the intervention. LCC allows to collect this relevant information using only one input, making sure that the eco-efficiency scores now obtained represent more complete information with reference to the sustainability of the retrofitting project. Model#1, then, proposes holistic eco-efficiency scores representing which intervention produces less CO_2 emissions and more final energy saving, taking equal the total value of the retrofitting project.

Clearly, this is only a preliminary study because, in order to identify which could be the optimal solution, other information should be taken into account, especially if the aim is to consider the whole impact of the intervention. Indeed, retrofitting interventions represent a deep renovation of building with the aim not only to recovery energy but also to improve the quality of life and the health status of occupants. For this reason, the spillovers cannot be restricted to the saving of energy and to the emissions reduction because if the air is cleaner, the whole population takes advantages. Last but not least, the financial recovery is one of the most relevant key-point of retrofitting because expenses for these interventions are a real investment for people that expect to recover them. The approach proposed in this manuscript considers only some aspects of good effects of retrofitting. However, if data will be available, it would be interesting to build a composite index where each indicator represents a single aspect of interventions. In this manner, a complete evaluation of retrofitting spillovers will be pursued.

Considering the present analysis, next steps will consider two issues: from the one hand, the possibility to collect more data on retrofitting interventions can improve the robustness of eco-efficiency scores and, at the same time, a bigger sample size could allow to rethink to the input-output space introducing more input in the model.

From the other hand, once defined the eco-efficiency scores, it will be interesting to consider these scores together with other characteristics of solutions not considered in the definition of the model.

For instance, the primary energy consumption is a very relevant information in evaluating the sustainability of retrofitting interventions and it could be considered as a bad output or an input in the DDF model. However, in general, a simpler input-output space allows to obtain more readable eco-efficiency scores, then the idea could be to cross, for each observation (i.e., retrofitting intervention), the value of scores and of primary energy consumption. Plotting this information on a Cartesian graph, it would be possible to identify the interventions with a lower value of score (i.e., more efficient) together with a lover primary energy consumption, so that the observation nearest to the origin of axes.

This simple way to cross data allows visualizing immediately the optimal solutions considering not only the eco-efficiency but also other relevant information, as the primary energy consumption. In this manner, the user will be able to choose among different packages of solutions (POS). Indeed, the purpose of crossing data will provide a taxonomy of POS based both on eco-efficiency scores and primary energy consumption. POS are different among them not only for spillover effects but also for necessary financial investments, then consumers have to evaluate which is the more suitable.

Considering the global economic impact, once selected the optimal solution in each POS, it would be possible also estimating the economic recovery in terms of CO_2 and of total energy consumption. Indeed, one of the main goals of European Community is the reduction of pollutions and in particular of carbon dioxide (CO_2). The EU ETS (i.e., Emission Trading Scheme)[5] is a market where emission allowances of CO_2 are exchanged among firms and then it provides the economic value of CO_2. Starting from these data, we can simulate which could be for each case-study the total economic value of CO_2 emission saved. In this manner, all stakeholders of retrofitting interventions will clearly understand all the positive effects of renovations from all points of view.

The strength of our approach is the union of two well-known standard techniques with the aim to define the best POS for each climate zones. In addition, the DDF is a very flexible solution that can be defined on the base of available data and considering each time a different definition of input-output space (i.e., the technology adopted). At the same time, non-parametric techniques suffer from some weaknesses. First of all, the robustness of results depends from the sample size and data quality. In addition, from the technical point of view, these are deterministic methods and the bootstrapping methodology does not solve the problem of the absence of the stochastic noise due to deterministic approach (Färe & Grosskopf, 1997; Coelli, 1998; Cooper & Lovell, 2000). The application of stochastic frontiers could be a good solution but they assume initial hypotheses difficult to test when the sample size is very little. Furthermore, the sample size can affect also the effectiveness and robustness of econometric tests on parameters (Daraio & Simar, 2007). However, these problems on stochastic frontiers can be overcame by a bigger sample size and in this case, literature suggests many studies comparing the two methodologies (Reinhard, et al, 2000; Lansink et al, 2014). In general, literature encourages research using DEA methodology and hybrid models because results highlight that benefits are bigger than costs of applications (Song et al., 2012).

Finally, it is clear that which proposed is not the classical Life Cycle Assessment analysis, but literature suggests that hybrid models can reach optimal results in defining criteria for decision analysis for sustainability assessment (Iribarren et al., 2010; Martín-Gamboa et al., 2017).

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[5] For a deeper description of the EU ETS market see the website of European Community: https://ec.europa.eu/clima/policies/ets_en

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Numeri precedenti

ABSTRACT

The paper proposes a preliminary analysis of a combination of two very interesting techniques used for assessing the economic and environmental sustainability of retrofitting interventions in the building sector and their eco-efficiency.

Indeed, one of the most popular methodologies proposed by the literature is the Life Cycle Assessment (i.e., LCA) because it considers not only costs and investment necessary for an intervention but also its spillovers on environment and society. For this reason, the LCA can be considered a technique able to guarantee a holistic assessment of retrofitting. However, data required for LCA are not always so easy to find and the necessity to evaluate the holistic impact of the intervention remains unsolved.

This paper suggests a hybrid methodology for evaluating different solutions of retrofitting interventions combining results from Life Cycle Costing (LCC) with those from the non-parametric technique of the Directional Distance Function (DDF).

The simplicity but, at the same time, the completeness of these methodologies allow to obtain efficient scores that can help to evaluate the holistic impact of retrofitting interventions on buildings, in particular in terms of energy savings and less CO2 emissions in the environment.

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