A data-driven multicriteria decision making tool for assessing investments in energy efficiency

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Abstract
Mainstreaming energy efficiency financing has been considered a key priority during the last decade among several stakeholders. The capability offered by Multicriteria Decision Analysis to integrate cross-domain financial and energy consumption data, combined with statistical analysis techniques and data abundance, contributes to building the necessary market confidence in energy efficiency projects and make them an attractive investment asset class. In this context, the aim of this paper is to propose a solid methodological framework in order to support the financing procedure of energy efficiency investments, and to identify improved grant financing plans, considering a series of factors which are of vital importance for the sustainability of such actions and the limitation of investment risk. A decision support tool, developed in Python, is presented which implements the suggested methodology, improving the decision making for the investor in terms of the percentage of grant financing per project. The developed methodology has been applied on a reliable dataset of energy efficiency projects from several cities in Latvia, where the actual performance of the investments is exploited. The application of the methodology has resulted in a financing plan which achieves about the same energy savings, while bringing 15% reduction of the energy efficiency investments’ cost.

Keywords Decision support · Energy efficiency · Energy management · Investment financing · Multicriteria decision analysis · TOPSIS · Data analytics

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1 Introduction

Current climate change threats and increasing CO₂ emissions, in particular from the building stock, represent a context where it is necessary to act upon and provide efficient manners to manage energy consumption and generation in buildings and contribute to a decarbonised economy (UNEP 2020). Nearly 97% of the building stock in the European Union (EU) is not considered energy efficient (less than 3% of the building stock in the EU qualifies for an A-label) (BPIE 2018), 75–90% of those standing today will still be in use in 2050, given that the construction rate is overall low (BPIE 2017), with low demolition rates (0.1% per year), low renovation rates [1.2% per year (EC 2015)], and an EU building stock inexorably aging (EC 2018) with 75% of the actual EU buildings stock built before 1990.

While new buildings can be designed and constructed to be able to produce living spaces with lower energy demand and usage, and while also considering that about 84% of the total building energy (WBCSD 2007) is typically consumed during the operational phase (assuming a building life of more than 50 years), the biggest impact on the energy demand can be achieved by improving the energy performance of the existing building stock, through increasing the number and the rate of deep energy renovation and promoting energy management (with expected savings of 60% or more) (Gonzalez et al. 2016).

Energy efficiency plays a crucial role in achieving the overarching aim of the EU’s Green Deal towards “climate-neutrality” by 2050. “Energy Efficiency First” or “Efficiency First” principle can also play a game-changing role in the energy transition (Marinakis et al. 2020a, b). The EU has already stressed the importance of scaling up investments in energy efficiency to avert climate change (Doukas et al. 2014). More specifically, the European Commission (EC) estimates that to achieve the newly agreed 55% climate target by 2030, around 275 billion of investments per year are needed, most of them in energy efficiency (EC 2020).

However, increasing the financial institutions’ deployment of capital in energy efficiency investments remains still a challenge (Doukas et al. 2021). Energy efficiency projects are often fragmented, with high transaction costs, and with no evidence-based platform that would allow investors and financial institutions to assess the risk, the financial performance of the investments, as well as the impact on energy efficiency (Zancanella et al. 2018). Partly due to the heterogeneity of energy efficiency investments and to the immaturity of the market for such investments, the relative costs for project development, finance documentation, processing and aggregation (together “transaction costs”) are high, making entry into this business unattractive for many financial institutions (EEFIG 2015). The investment institutions lack the technical understanding of the essence of energy efficiency investments; this often creates a lack of trust in such investments, acting as a barrier to including energy efficiency projects in the investment portfolio, even though they are often robust, with a guaranteed return (Karakosta et al. 2021).

Mainstreaming energy efficiency finance is considered as a key priority (Doukas 2018). The capability offered by Multicriteria Decision Analysis
A data-driven multicriteria decision making tool for assessing (MCDA) to integrate cross-domain financial and energy consumption, combined with statistical analysis, is the key for building the necessary market confidence in energy efficiency projects and making them an attractive investment asset class. Many studies are focusing on energy efficiency measures from many aspects, such as predictive control measures for energy efficiency and comfort optimization (Yang et al. 2020), smart device architecture towards enhancing buildings’ energy performance (Cannavale et al. 2020) and energy consumption prediction in the residential sector focusing on sustainability issues (Pham et al. 2020). Additionally, several frameworks have been implemented based on the innovative idea of green bonds (Azhgaliyeva et al. 2020), attempting to overcome the inability to finance upfront costs of energy renovations in residential buildings (Bertoldi et al. 2021), while other tools incorporate a cross-sector approach for green financing (Papapostolou et al. 2020a, b). The use of historical data pooled from major market segments can encourage more investments in energy efficiency, de-risking investments (Marinakis 2020; Marinakis et al. 2020a, b; Sarma et al. 2022).

In this context, the aim of this paper is to propose a solid methodological framework in order to support the financing procedure of energy efficiency investments, and to identify improved grant financing plans, considering a series of factors which are of vital importance for the sustainability of such actions and the limitation of investment risk. A decision support system (DSS), developed in Python, is presented which implements the suggested methodology, improving the decision making for the investor in terms of the percentage of grant financing per project. The developed methodology has been applied on reliable dataset of energy efficiency projects from several cities in the country of Latvia, where the actual performance of the investments is exploited.

The rest of the paper is organised as follows. In Sect. 2, the proposed methodological framework and the relevant DSS are presented. In Sect. 3, the dataset in which the proposed framework was applied and tested, is described. In Sect. 4, the results of the experimental application, along with a comparison of the proposed financing plan with the implemented financing plan, are presented. In Sect. 5, the contributions and conclusions of the current study are discussed, respectively.

2 Methodology

The proposed methodological framework is presented in Fig. 1. It aspires to combine existing techniques and methods from the MCDA field with a set of indexes which measure the efficiency of an investment and have been selected based on statistical analysis conducted on the available dataset and in close collaboration with investors. According to Fig. 1, a new proposed energy efficiency project is described by various information such as building location, construction year and functionality, cost of energy efficiency actions, baseline and actual energy savings achieved etc. These data are directly compared with respective data from past energy efficiency actions on buildings, exploiting the TOPSIS method which is applied based on four criteria: Energy reduction per cost, energy reduction
percentage per cost, building age and building consumption per heating area. Finally, the project is classified into one of the five categories according to its performance on the MCDA methodology. After the investment’s approval, the details of the new project are fed back to the pool, completing the dynamic procedure of the proposed DSS.

MCDA belongs to the scientific field of Operational Research (OR), aiming to provide models that are capable of dealing with multivariable optimisation problems, incorporating all different parameters of the problem. The most crucial components of each MCDA problem are the detailed and careful analysis of the optimisation criteria and the proper selection of the MCDA method that will be exploited. The selected MCDA method for the development of the proposed tool is TOPSIS.

TOPSIS belongs to the family of compensatory methods, unlike other MCDA techniques such as ELECTRE and PROMETHEE (Xidonas et al. 2021). Thus, relatively poor performance of an alternative in certain criteria can be compensated by relatively high performance in some other criteria (Banihabib et al. 2017). On the contrary, non-compensatory decision-making methods eliminate alternatives that do not perform well to a particular criterion. Compensatory methods fit better in this specific problem, as it is not desirable to cut off an energy efficiency project that has a high aggregated performance because of low score in a specific criterion. For example, a project that shows poor performance in the index of Building Age but performs very well in terms of Energy Reduction Percentage per Cost and Building Consumption per Heating Area should not be eliminated. Another advantage of the TOPSIS method is the straightforward way of performing the comparison among the alternative actions, as well as the relatively small computational complexity compared to other more complex MCDA methods. The abovementioned attributes
of TOPSIS render it as the most suitable method for handling large amount of data which is a main limitation of the problem.

2.1 The selected evaluation criteria

The adoption of energy efficiency measures is influenced by different categories and types of contextual factors (Spyridaki et al. 2020). The proposed methodology is based on four criteria which take into consideration the most crucial parameters of both the building in which the investment is carried out and the investment itself. After studying the available datasets of energy efficiency projects from several cities in the country of Latvia (location, economic sector, building construction year, building functionality, heating area, energy efficiency measures cost, energy consumption (baseline), energy savings (expected / actual), as well as the correlation of a series of factors to the effectiveness of the energy efficiency investment, and in communication with the Decision Makers (DMs) and experts in the field, the most influential indexes which affect the prosperity of such an investment were extracted.

2.1.1 Energy reduction per cost

The Energy Reduction per Cost index (KWh/€) is one of the most important factors which should be considered. It indicates the amount of energy savings projected with the investment cost. The Energy Reduction per Cost index is described by the following equation:

\[
\text{Energy Reduction per Cost} = \frac{ES}{TC}
\]  

(1)

where \( ES \) indicates the actual energy savings achieved and \( TC \) the total cost of the investment.

2.1.2 Energy reduction percentage per cost

The Energy Reduction Percentage per Cost (€\(^{-1}\)) index indicates the percentage of energy reduction per unit of investment cost. The Energy Reduction Percentage per Cost index is described by the following equation:

\[
\text{Energy Reduction Percentage per Cost} = \frac{ES}{EC_{\text{before}} \times TC}
\]  

(2)

where \( EC_{\text{before}} \) indicates the energy consumption of the building before the implementation of the energy efficiency measures, \( ES \) the actual energy savings achieved after the implementation of the measures and \( TC \) the total cost of the investment.

2.1.3 Building age

Despite the fact that the abovementioned indexes are of great importance for the evaluation of energy efficiency investments, there are two more factors which can
be considered during the comparison of the alternative actions. The first of those factors is related to the building age, which is an important factor for investors. The older buildings usually are less energy efficient, thus, offering opportunities for significant improvements even with a series of small-scale measures.

### 2.1.4 Building consumption per heating area

Finally, the fourth evaluation metric to be considered is the Building Consumption per Heating Area index (MWh/m²). This metric aims to normalise the consumption per building based on the building’s heating area, in order to make the buildings’ consumption comparable. Buildings with higher consumption per heating area are capable of achieving greater consumption improvements, constituting better investments opportunities. The Building Consumption per Heating Area index is described by the following equation:

\[
\text{Building Consumption per Heating Area} = \frac{EC_{\text{before}}}{BHA} \tag{3}
\]

where \(EC_{\text{before}}\) indicates the energy consumption of the building before the implementation of the energy efficiency measures and BHA is an acronym for Building Heating Area.

### 2.2 The TOPSIS method

Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a commonly used MCDA method which belongs to the Multiattribute Utility Theory (MAUT) subfield of MCDA. It was originally developed by Hwang and Yoon (1981), but many variations of the method have been developed over the years (Chen 2000, 2019), with the most indicative one being found in the development of Fuzzy TOPSIS (Papapostolou et al. 2017, 2020a, b; Boran 2017). TOPSIS, in its various forms, has been widely used for energy efficiency related problems (Meng et al. 2018; Chamodrakas and Martakos 2011), as well as to support decision-making in other sectors, such as utilisation of energy sources (Alidrisi and Al-Sasi 2017), electricity generation (Brand and Missaoui 2014; Büyüközkan and Güleryüz 2017), environmental assessment (Mourhir et al. 2016), energy poverty (Arsenopoulos et al. 2020) and transport (Sakthivel et al. 2015).

In the context of this paper, TOPSIS is utilised in order to provide a descending ranking of the alternatives based on the four criteria which were analysed in Sect. 2.1. The input of the algorithm are the alternatives (n) of the problem, the evaluation criteria (q), the offsets for the evaluation criteria \((w_i)\) and the evaluation matrix which includes the performance \((f_{ij})\) of each alternative \((i)\) in each criterion \((j)\).

According to Sarmas et al. (2020), the steps of the TOPSIS method are described as follows:
• Step 1: Normalised Decision Matrix: The formulation of the normalised decision matrix is a necessary process in order to ensure that data are in the same scale. Given the $n \times q$ decision matrix, the new normalised decision matrix can be calculated using the matrix normalization formula described by Eq. 4 for each element $f_{ij}$ of the initial matrix:

$$r_{ij} = \frac{f_{ij}}{\sqrt[2]{\sum_{k=1}^{n}f_{kj}^2}}$$

(4)

It is evident that the matrix normalisation formula described above is not the only available normalisation mechanism. Several other formulas have been proposed for creating the normalised decision matrix (Sarraf et al. 2013), such as the fuzzy normalisation, sum normalisation and min–max normalisation formulas. A comparative evaluation of the effects of the different formulas has been developed by Chakraborty and Yeh (2009). The formulas of sum normalisation and min–max normalisation are presented in Eqs. 5 and 6 respectively:

$$r_{ij} = \frac{f_{ij}}{\sum_{k=1}^{n}f_{kj}}$$

(5)

$$r_{ij} = \begin{cases} 
\frac{f_{ij} - f_{j}^{\text{min}}}{f_{j}^{\text{max}} - f_{j}^{\text{min}}}, & \text{for benefit attributes} \\
\frac{f_{j}^{\text{max}} - f_{ij}}{f_{j}^{\text{max}} - f_{j}^{\text{min}}}, & \text{for cost attributes}
\end{cases}$$

(6)

• Step 2: Weighted Normalised Decision Matrix: The relative significance of the model’s criteria can be quantified by transforming the normalised decision matrix into the weighted normalised decision matrix. The weighted normalised decision matrix is created by multiplying each element of the normalised decision matrix’s column by the offsets, as follows:

$$t_{ij} = r_{ij} \times W_j, \text{ where } W_j = \frac{w_j}{\sum_{k=1}^{q} w_k}$$

(7)

• Step 3: Positive and Negative Ideal Solution: The positive ideal solution $A^+$ and the negative ideal solution $A^-$ can be computed from the weighted normalised decision matrix with the following formula:

$$A^+ = \{\{\min(t_{ij}), i = 1, 2, \ldots, n | j \in J_\_\}, \max(t_{ij}), i = 1, 2, \ldots, n | j \in J_+\}$$

(8)

$$A^- = \{\{\max(t_{ij}), i = 1, 2, \ldots, n | j \in J_\_\}, \min(t_{ij}), i = 1, 2, \ldots, n | j \in J_+\}$$

(9)

where $J_+$ is the subset of maximisation criteria and $J_-$ is the subset of minimisation criteria.
• Step 4: Separation Distance from the Positive and Negative Ideal Solution: Let \( t^+_k \) be the positive ideal value and \( t^-_k \) the negative ideal value for criterion \( k \). The separation distance (\( L^2 \)—Distance) of each alternative from the positive and the negative ideal value, respectively, are calculated as follows:

\[
S^+_i = \sqrt{\sum_{k=1}^{q} (t_{ik} - t^+_k)^2}
\]

\[
S^-_i = \sqrt{\sum_{k=1}^{q} (t_{ik} - t^-_k)^2}
\]

• Step 5: Relative Closeness to the Ideal Solution: The relative closeness to the ideal solution can be computed by comparing the separation distance from the ideal and the negative ideal solution. The higher the relative closeness to the ideal solution, the better is the ranking of the alternative. The formula for computing the relative closeness to the ideal solution for alternative \( i \) is given by the following equation:

\[
C_i = \frac{S^-_i}{S^+_i + S^-_i}
\]

2.3 Labelling energy efficiency investments

After the ranking of the TOPSIS method is produced, each alternative has been evaluated with a score and a ranking position. The next step of the proposed framework includes the creation of five distinct classes in order to efficiently label new investments. The aim of the proposed financing plan is to label new investments within the following classes: {Strongly Negative, Negative, Neutral, Positive, Strongly Positive}. The limitation adjustment between the different classes is conducted according to the TOPSIS method results.

2.3.1 Default categorisation

The classic approach indicates the equal distribution of alternatives between the five classes. This means that the 20% of the alternatives with the highest ranking should constitute the “Strongly Positive” class, the following 20% of the alternatives should constitute the “Positive” class, etc. Finally, the alternatives with the lowest scores would constitute the “Strongly Negative” class, implying the least favoured actions to invest in. Each time a new energy efficiency action should be evaluated, the respective alternative is given a TOPSIS score and according to this score it is labelled in one of the classes.

2.3.2 Adjusted categorisation

Any DSS should incorporate the DM’s preferences, trying to be as much flexible and configurable as possible. In this respect, an advanced functionality is also developed,
enabling the DM to adjust the classes limits making the tool more flexible in any direction (either stricter, or more lenient). Consequently, the number of alternatives per class from the train set can be configured by the user. If, for example, the DM wishes to apply a strict classification, he/she could configure that the “Strong Positive” class must be made of only the top 5% of the alternatives. On the contrary, for a more lenient approach, he/she could adjust the limit of the “Strong Positive” class to 30%, or even reduce the percentage of the alternatives of the “Negative” and “Strong Negative” classes. Finally, this functionality allows the DM to reduce the number of classes. Setting for example the percentage of “Neutral” to zero, then the classes are automatically reduced to four, resulting in a less diverse labelling of the energy efficiency actions.

Fig. 2 DSS tool flowchart
2.4 Decision support tool and user interaction

The interaction between the use and the decision support framework has been maintained as simple as possible. The whole process from importing the input data to the benchmarking of the new project is composed of four discrete steps, as shown in Fig. 2.

Firstly, the user should insert the input parameters of the new investment that will be assessed. The necessary parameters are the building construction year, the total heating area, the total energy savings of the project, the cost of the energy efficiency measures and the energy consumption before the renovation takes place. The tool, then, calculates the necessary indexes of the project as described in Sect. 2.1. The second step of the user interaction process requires the user to assign offsets to the four optimisation criteria according to his/her preferential profile. Based on the user’s weights, the TOPSIS method is performed, creating the ranking of the investments and the default boundaries of the five classes, subsequently.

The third step of the methodology enables the DM to adjust the default boundaries of the 5 classes, customising the labelling of the investments. More specifically, the user interacts with the DSS tool configuring the percentile of projects per class. This choice affects the labelling process, rendering it either stricter or more lenient, or even reducing the number of classes as stated in Sect. 2.3. Finally, in the fourth step the DSS produces the label of the energy efficiency investment, labelling the project into one of the five predefined classes. It is worthwhile mentioning that the DSS tool follows an interactive approach enabling the refinement of both the weighting factors of the TOPSIS method and the categorisation type at any stage of the decision making process.

Following the project assessment of the proposed project, the most important details and characteristics of the project, including building construction year, heating area, project cost and energy consumption among others, are saved in order to be exploited for the implementation of the methodology on future projects. Thus, a big pool of assessed projects is developed, which is of great importance for the successful application of the TOPSIS method and the labelling of energy efficiency actions on new buildings. In the final version of the implemented methodological framework, project information will be stored in a database where all data will be retrieved from.

From a technical point of view, the presented methodological framework has been implemented in Python 3.0 programming language. Python is a general-purpose, high-level language, which is extensively used in the academic field. It provides a series of supplementary libraries which have been used for the implementation of the proposed DSS. More specifically, the Pandas open-source library was used for importing the dataset as a DataFrame object, the NumPy library which is a set of functions for scientific computing was used for the statistical analysis of the available data and Matplotlib was exploited for the production of high-quality figures and visualizations.
The validity of the proposed methodological framework was tested in detail within a pool of 312 energy efficiency projects, which were gathered and will be analysed in this section. The utilised dataset was sufficiently pre-processed through data cleaning and analysis, in order to be suitable for the experimental application of the proposed framework. The energy efficiency projects that have been gathered stem from numerous cities in Latvia and have all been partly grant financed from 2009 until 2015.

The most important information that is available on the utilised dataset, which has been used for statistical analysis (correlation, mean values, variance etc.) and for training the proposed model is presented in Table 1.

As shown in Table 2, most buildings included in the dataset are used as educational institutions, factories and preschool educational institutions, while the majority of the buildings are placed in Riga, Daugavpils and Rezeknes. 239 of the renovated buildings belong to the public sector, while 73 buildings belong to the private sector. Moreover, it should be highlighted that the most common renovation actions that were performed are: (a) renovation of the building’s enclosing structures, (b) heat supply and ventilation system renovation (c) energy efficient lighting and (d) wood chips, biomass pellets and straw boiler house.
3.2 Statistical analysis

The key attributes of the dataset which were used for training the model are the consumption of the building before and after the renovation actions, as well as the heating area of the buildings and the investment cost. Figure 3 visualises the age of the dataset’s building. 50% of the buildings were constructed during either between 1970 and 1980, or between 1980 and 1990, resulting in having old heat supply mechanisms and enclosing structures. This applies in a greater extent for...
even older buildings which would certainly provide bigger energy reduction in case that they could be financed.

Figure 4 shows the energy reduction and the investment cost of the buildings that are integrated in the experimental application of the model. The most valuable actions to invest in are placed in the lower right part of the figure, meaning that they result in high energy reduction while maintaining their cost at low levels.

We should note that there are investments with high cost which result in less than half of the energy reduction of other lower cost investments. Therefore, the need for an advanced methodology for financing energy efficiency actions is necessary.

Figure 5 includes a visualization of the energy consumption per heating area for the available buildings that we studied. The conclusion from this insight is that the majority of buildings keep this ratio in the range of 0.1–0.3. For buildings that the ratio lies above 0.3, this can be interpreted as excessive energy consumption, indicating that energy efficiency actions would be highly recommended.

Finally, before presenting the results of the empirical testing of the methodology, in Table 3 some basic statistics of the four evaluation criteria which are utilised, are presented. The index with the highest variance relatively to its mean value is the energy reduction percentage per cost, while, on the other hand, the least varying one is the building consumption per heating, as expected according to Fig. 5. The fourth column of Table 3 can be thought as the negative ideal solution for TOPSIS method.
before normalisation, because all four criteria are maximisation criteria, meaning that greater values are more preferable. The fifth column can be thought as the positive ideal solution, respectively. An investment that would ideally take these values for all four criteria would achieve the maximum score in TOPSIS ranking.

4 Experimental results

4.1 Empirical testing of the proposed methodology

For the experimental application of the proposed model we split the dataset into training set and test set, keeping 90% of the buildings as training set. Therefore, 280 buildings were used in order to train the model and extract the five classes, while 32 buildings were inserted to the model as test data and were labelled by the proposed algorithm.

In Table 4, we present the five classes which were created after running the model with the available training set using the default categorisation (each class should include equal number of investments). The offsets for the four criteria were assigned using the Simos method which is considered as an effective tool to assess the criteria importance weights in the field of MCDA (Siskos and Tsotsolas 2015). Therefore, in communication with the DM, the Energy Reduction per Cost and Energy Reduction Percentage per Cost indexes were considered the most important criteria and thus were assigned 40% weighting factor each, whereas Building Age and Building Consumption per Heating Area indexes were assigned 20% weighting factor each.

As mentioned above, the proposed methodological framework aspires to develop as a dynamic process, as more and more investments are assessed. In this respect, every time a new investment is labelled by the model, then it directly becomes part of the training set making the classes dynamically adjust based on new available data. The third column of Table 4 reflects the five investment classes after all 32 investments of the test set have been evaluated. The dynamic character of the proposed model is reflected by the fact the border for the “Strong Positive” class has decreased from 26.98 to 25.40% after the assessment of the test set investments, indicating that the assessed investments were not so worthy to invest, thus partly dropping the standards for future projects which will be evaluated.

Table 4 Investment classes based on the training and the whole dataset

| Class               | TOPSIS score (only training set) | TOPSIS score (whole dataset) | Proposed grant financing (%) |
|---------------------|---------------------------------|------------------------------|------------------------------|
| Strongly negative   | [0–13.02]                       | [0–12.32]                    | 10                           |
| Negative            | [13.03–16.85]                   | [12.33–15.98]                | 30                           |
| Neutral             | [16.86–20.65]                   | [15.99–19.83]                | 50                           |
| Positive            | [20.66–26.97]                   | [19.84–25.39]                | 70                           |
| Strongly positive   | [26.98–100]                     | [25.40–100]                  | 90                           |
Finally, in the last column a Grant Financing Plan (GFP) is proposed. According to the proposed scheme, the investments of the “Strongly Positive” class should be financed with 90% of their total cost, the investments of the “Positive” class should be financed with 70% of their total cost etc. It is obvious that the proposed financing scheme could be adjusted according to the preferences of the DM, as well as other restrictions that may be introduced such as the available budget.

4.2 Comparison of the proposed and the implemented financing plan

The dataset that was used for the experimental application consists of a portfolio of investments which have already been Grant Financed from 2009 until 2015. The purpose of this section is to compare the already implemented grant financing plan with the proposed plan which stems from the methodological framework.

Figure 6 shows the energy reduction per cost index (KWh/€), which is a key metric of an investment’s efficiency, against the grant financing ratio for a subset of the implemented actions. It is clear that several projects which have relatively low investment efficiency have been grant financed with more than 60% (grant financing ratio greater than 0.6), while other projects with high impact in terms of energy efficiency have received significantly less financing.

Another important insight stemming from Fig. 6 is that investments with high energy reduction percentage per cost may also be underfinanced.

For example, the yellow dot in the centre of the Figure implies an energy efficiency action with high investment efficiency (the respective index has a value
greater than 10), which has received financing with ratio below 0.5. On the other hand, there are multiple inefficient investments which have been overfinanced.

Figure 7 visualises the implemented financial ratio against the TOPSIS score that was generated from the model, for both the implemented grant financing plan (left figure) and the proposed financing plan according to the proposed algorithm (right figure). The left figure shows that although there are several energy efficiency projects which were rightfully financed, there are many investments with low score which could have received lower financing, if any. The right figure shows the implementation of the proposed plan, where, as expected, financing is distributed according to the investment’s label. Consequently, the investments with the lowest cost have been labelled as “Strongly Negative” and they should be financed with the lowest ratio.

Finally, we attempt to compare the two grant financing plans in terms of investment efficiency. Such a comparison would be meaningful if energy saving due to financing was calculated. For example, an investment with energy saving of 10 MWh which was received 30% financing, provides 3 MWh energy saving due to financing. The insights of this comparison are depicted in Table 5.

We can identify that the total budget in the case of the implemented financing plan is more than 15% higher compared to the proposed financing plan, while on the other hand the energy saving difference is insignificant. This leads to the fruitful insight that the proposed plan results in about 1.1 KWh/€, while the

| Table 5 | Comparison of implemented and proposed action plans in terms of budget and energy saving |
|---------|-------------------------------------|
|         | Implemented financing plan | Proposed financing plan |
| Total budget (€) | 59,435,964.78 | 48,834,203.21 |
| Energy saving due to financing (MWh) | 53,906.5 | 53,275 |
| Energy saving due to financing per total budget (KWh/€) | 0.907 | 1.091 |
implemented one offers only 0.9 KWh/€. Last but not least, this difference would be even higher, if we had assigned even bigger weights in the Energy Reduction per Cost Index.

5 Conclusions

In this paper, an integrated methodological framework for assessing and labelling energy efficiency investments was presented, based on a series of criteria stemming from indexes such as the investment cost and the energy saving achieved, among others. Thus, we define investments that have an extremely strong capacity to meet their energy saving targets, already from their conceptual phase, when they are still considered as project fiches, from the funding institutes.

The recommended approach aspires to reduce the uncertainty linked to energy efficiency investments, which can be attributed to the lack of relevant skills and inability to properly assess investments through a multicriteria environment. The systematic benchmarking offered by the designed DSS paves the way towards financing investments with high potential of meeting their energy efficiency targets.

The presented work in this study aims to strengthen debt and equity financing of energy efficiency projects, providing investors, financiers and project developers the opportunity to evaluate key performance indicators directly and easily for projects and to label the candidate investments. The main advantage of the designed tool is that it enables the DM to participate during the decision-making process incorporating his/her preferential system in the methodology, instead of using the tool as a black box.

However, the current version of the proposed DSS lacks a user interface, which will be available in the final version making the user interaction with the tool more direct, enabling the deployment, up-scaling and generalization of the tool, as well as the storage of the available data in a database. It is important, though, to consider the architecture of such database because of the large volume of data that will be potentially stored. Therefore, a distributed database management system can also be adopted instead of the traditional sequential models, where information can be structured and logically interrelated across many sites, while a common interface to access the distributed data is available.

In future work, except from finalizing a user-friendly interface, the focus should be on creating even more specialised and sophisticated benchmarks per country, investment type and sector, in order to achieve a more precise and detailed comparison between the alternative actions and make possible to rate project fiches by individual performance indicators or in an aggregated manner. Moreover, future research should also focus on optimizing the values for certain parameters of the problem. For instance, the selection of five discrete classes of energy efficiency projects has been based on existing literature, offering great potential for further investigation of the optimal number of classes. Finally, one should not neglect the constantly increasing momentum of machine learning algorithms which can generate useful information and indicators to the investors for energy efficiency financing.
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