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MODEL FOR RETROFIT CONFIGURATION SELECTION USING MULTIPLE DECISION DIAGRAMS

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ABSTRACT

The paper demonstrates the use of Multiple Decision Diagrams (MDDs) in consideration of building energy retrofit options. Candidate retrofit alternatives including associated key performance indicators (KPIs) (*e.g.* cost, energy, embodied carbon) can be compiled into MDDs where various performance implications can be effectively illustrated and KPI trade-offs explored. We argue MDDs are flexible supporting a wide range of computations around the decision process. Significantly, we show KPIs can also be used as constraints in the search for satisfactory retrofit configurations and conclude that the MDD approach complements existing methods of optimising building energy retrofit options by providing a reduced initial search space.

INTRODUCTION

There is widespread consensus that climate change is occurring and that anthropogenic greenhouse gases (GHG) are contributing significantly (Solomon *et al.* 2007). Consequently, there is international agreement that GHG emissions should be reduced to stablise atmospheric conditions and prevent dangerous interference with the climate (UNFCC 1992).

The largest single source of greenhouse gases is the built environment, which accounts for up to 40% of global energy consumption and associated emissions (Cheng *et al.* 2005). As a consequence, improving building energy efficiency is seen as offering greater potential for energy savings and greenhouse gas reduction than any other single domain (EC 2010).

The lifespan of buildings is such that 80% of European buildings in use today will still be used in 2030 (EC DG-Research and Innovation 2010). Consequently constructing new buildings to high energy-efficient standards on their own will not provide the required building stock energy performance improvements. Accordingly, substantial retrofitting for energy conservation and improved efficiency to existing buildings is needed.

Choosing the right set of components, systems or interventions in the design of a new build or retrofitting energy efficiency measures to an existing building, is a complex problem. It involves multiple constraints in the context of the existing building and the specific requirements / preferences of clients. These assessment criteria include energy performance, cost, aesthetics, environmental impact, structural limitations, planning restrictions *etc*.

CONTEXT

No single configuration will maximise/minimise all the requirements above. There are too many trade-offs between the various building energy retrofit assessment criteria for designers to manually track. Typically, the objective of a building energy retrofit project is to maximise energy efficiency, thereby minimising operating costs while minimising capital expenditure (now and in the future). At the same time the existing building's context must be considered and specific preferences of the client expressed. Significantly a life cycle perspective is increasingly being adopted with respect to these assessment criteria, particularly so with whole life carbon considerations and embodied carbon (Lane 2007, Sturgis and Roberts 2010, Jones 2011).

In such types of decision-making, the modelling and articulating of complex trade-offs is of great importance for any system chosen to support the designer. Finding the optimal solution in such a subjective area (trade-offs are often difficult to put a value on) requires innovative solutions (algorithmically and visually) with respect to showing the designer what is available as he/she introduces constraints and expresses preferences while the building design is undertaking.

Generally, this type of problem is a multi-criteria decision one and traditionally two approaches have been adopted in an effort to consider more than one criterion simultaneously (Triantaphyllou 2002, Kahraman 2008, Wang *et al.* 2009). The first is where all but one criterion is handled as a constraint and the final one made the objective. The second approach is where a weighted sum of each criterion is added to the objective function, reflecting the perceived importance of each. Both approaches require *a priori* information from designers: boundary conditions for the constraints and/or weights for the performance criteria. With little knowledge about the performance space of solutions in advance, designers may find it difficult to set appropriate values for those required inputs. Furthermore, only one optimal solution is obtained for each run if the performance criteria are treated separately or coupled together into one meta-criterion. In these models, the designer cannot learn about the impact of the marginal change of one criterion on another just from a single optimal solution. Therefore, it is difficult to make cost-effective decisions without knowing the trade-off relationship between economic and environmental performance for example. Both methods mainly draw on Mathematical Programming as the way to solve it once modelled.

Many of these previous issues have more recently been addressed using evolutionary algorithms. Consequently, many papers on this subject compete on which variation is the most appropriate across different sets of criteria. Wang *et al.* (2005) propose a genetic algorithm approach where the two criteria objective (life cycle cost and life cycle environmental impact) is decided by a Life Cycle Assessment model. This algorithm results in a Pareto style solution, which provides the user with a spread of solutions for analysis. Wright *et al.* (2002) also use a similar approach for a smaller problem (in building terms) of the optimum pay-off characteristic between the energy cost of a building and the occupant thermal discomfort. Fesanghary *et al.* (2012) use another method based on a harmony search algorithm, which minimizes the life cycle cost and CO_2 equivalent emissions of the building. In all these cases the search is over building interventions which are taken as variables to optimise some KPI.

All these approaches have registered theoretical results, but little evidence of commercial acceptance. They are also restricted in the number of evaluation criteria considered.

The research presented in this paper advances the scope of these approaches through a more pragmatic approach to give the user more control over searching for an initial solution, less upfront information required and a wider range of KPI's. Most importantly, much of this can be automated to allow more design options to be incorporated easily and quickly. However, no compromise is made around accuracy with energy performance data provided via use of the whole building simulation tool of EnergyPlus, embodied carbon figures sourced from published data sources (*Hammond and Jones 2011*), *etc*.

After further explanation of the MDD approach it will become apparent that a relational database approach is also comparable to store all the potential design examples. However, although access to an individual design can be fast using SQL, the type of search we require to do has been optimised within an MDD and therefore performs faster, especially if the size of the MDD is much smaller than the number of solutions. Equally, propagation and optimisation are not natural parts of database languages – instead these would have to be implemented in SQL and in effect re-implementing MDD with the additional performance overheads associated with maintaining a database.

METHODOLOGY

Multiple Decision Diagrams

In our approach, building energy retrofit solutions in the form of sets of interventions and their 'costs' are compiled into an MDD, described by Wilson (2005), extending the approach of Amilhastre *et al.* (2002). A similar approach to representing solutions has also been taken by Nicholson *et al.* (2006), but related to product catalogues as sets of 'solutions'. We believe that this is the first time the approach has been used on building energy retrofit design and for KPIs.

A Decision Diagram is a directed graph, having both a Source and Sink nodes. Each complete path from Source to Sink, represents a single solution. In our case this is a retrofit design solution for the building being considered, in terms of both the chosen interventions and the desired performance of the building (cost, energy saving, *etc*.). Each of these broad design choices has a number of possible values associated with it, which can be fixed, constrained or left free during the user's interaction with the MDD, as we explain below.

Table 1 presents a subset of possible retrofit solutions and associated costs for a case study building, discussed later. This data, along with associated performance and other relevant data *e.g.* embodied carbon, will be inserted into an MDD. Note that the option for making no intervention of a certain category can also be catered for, although not in the example we use in this section.

Table 1
Subset of Alternative Retrofit Options from Case Study

NO.	WINDOW TYPE	WALL INSULATION (mm)	ROOF INSULATION (mm)	COST (€K)
1	Double	67.8	100	200
2	Double	67.8	500	280
3	Double	125	100	230
4	Double	125	500	300
5	Triple	125	100	250
6	Triple	67.8	100	230
7	Triple	67.8	500	300

Figure 1 shows the option table converted into an MDD with each of the seven designs being represented by a unique path from Source to Sink. Figure 2 shows another, more compact representation of the same set of solutions and it is this ability to ‘collapse’ the MDD, which make them very efficient and scalable in processing certain types of user decisions. In both these examples, the source is associated with the windows choice and so the edges that connect to the next decision are labelled with the values of that decision, namely ‘double’ and ‘triple’.

Collapsing an MDD can be done without losing any of the information in the original graph. It is both *complete*, i.e. all solutions that were in the original graph are still contained in the collapsed graph, as well as *correct*, i.e. no invalid solutions are introduced.

There is no significance in having windows as the first choice and indeed, when the MDD is deployed, the user is not aware of any ordering. All categories and KPIs reside at the same level.

The next stage is associated with wall insulation and so its edges represent the two different thicknesses; and so on. Decisions can be switched around to try and achieve a more compact representation, which in turn improves the MDDs performance in use.

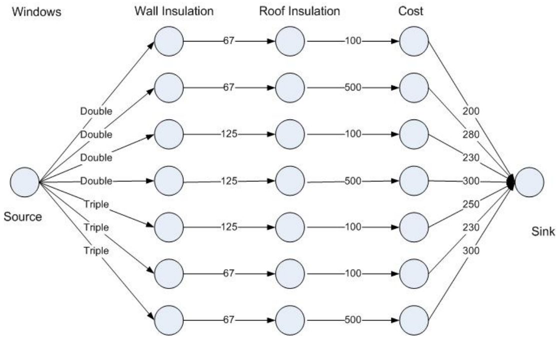

Figure 1 One Possible MDD from Table 1 Design-base

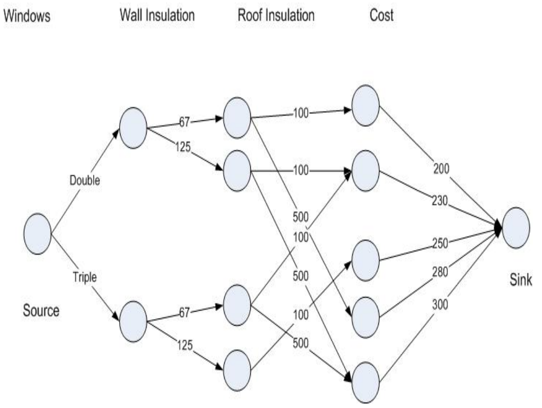

Figure 2 Another More Compact Possible MDD from Table 1 Design-base

Having compiled the information into an MDD representation, it remains to show how we can efficiently compute user’s queries.

Firstly, an MDD can efficiently return the number of possible designs remaining at any time, given a number of choices having already been made. This means that the user is informed the size of the remaining search space at any time. A high number of remaining designs would encourage the user to make further choices to reduce this to a number of choices, which the user can then compare individually. For example, hundreds of options cannot be evaluated manually. It would then require the user to impose additional preferences to reduce this number to a level, which can be evaluated by the user individually and allow more preferences to be taken into consideration. Conversely if the number of remaining designs is small, then the user may view these individually or relax a preference to open up other configuration options to explore.. In MDD terms, this is simply counting unique paths available through the network, which is done in linear time to the size of the network. Although our MDD contains only a few examples we would expect to generate many thousands of design alternatives – too many to view and comprehend as a whole.

Secondly, MDDs can invoke propagation between categories. When a particular choice/value is made for a design intervention, then all other associated edges of that choice in the MDD are removed. Further, some values in others choices may also become invalid, which is reflected in the elimination of edges. In Figure 3, we have chosen to find designs with cost less than €230k indicated by the removal of the edges representing €250k, €280k and €300k. All their supporting paths will also be removed, as they cannot be in the solution (again calculated in linear time) – this is propagation. The remaining edges therefore represent the possible values for decisions within this new space of designs and the number of unique paths equals the number of remaining unique solutions.

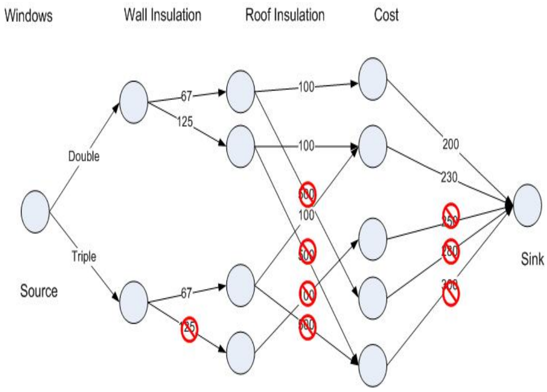

Figure 3 Propagation Following a User Imposed Constraint on the Cost

Thirdly, optimisation of any numerical decision simply becomes one of choosing the lowest (in the case of minimising) value and eliminating all the associated edges and propagating. This will leave at least one single path through the network representing the optimal set of decisions around the best value. In Figure 4, assuming that we have already chosen 125mm wall insulation and now want to know the remaining design interventions to give the minimum cost. Propagating around wall insulation of 125mm excludes a number of unsupported edges, including several in the cost category. A minimum cost of 230 is therefore proposed with a path or design of double-glazing, 125mm wall insulation and 100mm roof insulation. Each design is not created, but generated based on combinations of interventions and simulated to give their performances automatically also. In this way, we build up a 'space' of possible designs covering most of the avenues of exploration, designers may wish to explore. However, these designs are interlinked within the MDD.

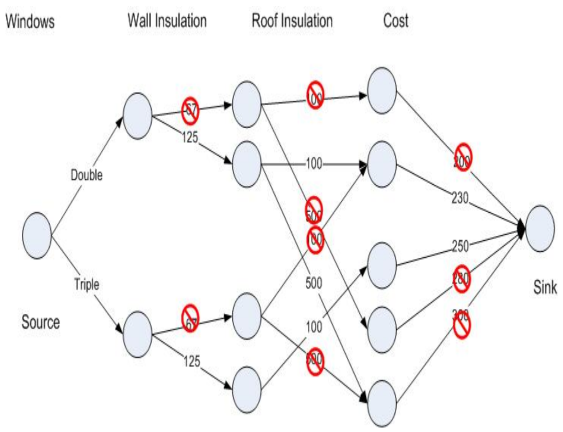

Figure 4 Optimisation of Cost Following Wall Insulation Selection

System Description

Preparation

In order to populate the MDD, energy retrofit design solutions are generated for the building of interest and the associated data collated. All types of quantitative data can be associated with the potential solutions, which results in system that can adapt as users' needs change. The accuracy of any interrogation of a MDD and the quality of the decision support is directly linked with the quality of the input data.

The case study discussed below considers embodied carbon in addition to cost and energy performance (energy savings or more correctly, avoided energy consumption); in this case the data to be included in the MDD would include:

- Equipment, material and commissioning costs. This type of information can be sourced from suppliers, contractors *etc*.
- Embodied carbon of the proposed interventions. This data can be sourced from a combination of supplier data *e.g.* Evironmental Product Declarations, databases *e.g.* Inventory of Carbon and Energy (Hammond and Jones 2011), *etc*.
- Energy performance of the solutions in various combinations estimated by whole building energy simulation using EnergyPlus [http://www.energyplus.gov]. The building data required to model the

In order to model the building, its operation and to simulate energy consumption a number of datasets are required including:

(i) Construction information to allow specification of building geometry, surfaces *etc.*;
(ii) Building use profile;
(iii) Details of heating, ventilation and air conditioning (HVAC) and related systems.

Besides this data describing the current state of the building and its usage, the user needs to specify the possible interventions. The format these need to be given in is the difference δ with the base situation.

In the case study, EnergyPlus input files (*.idf) were automatically created for each configuration including the baseline building. This enabled consideration of multiple interventions and computation of their combined effects

To achieve this, we require, without loss of generality, that the types of interventions are *independently describable*[1] within the input file. That is, changes required to the input files for an intervention of type *I* will not interfere with any intervention of a type *I≠J*. When this is the case (as is the case in all of our examples), a set of interventions δi ... δk can be automatically and correctly described in a single input file.

This data representing the various configurations and their performance is then converted into a MDD datastructure, which can then be interrogated by users using the Intellify™ MDD analyser. Much of this process is automated, especially around the whole building energy simulation software, which can be run many thousands of times based on discrete changes to the input files reflecting the different types of interventions being considered.

In Practice

Users select desired outcomes and set constraints, preferences etc. for which the MDD analyser presents the most satisfactory solution. Figure 5

[1] In the descriptions of two types interventions I and J interfere with each other, users can manually create an intervention type IJ that reflects the combined change

below presents the user interface and indicates how users can set constraints and seek desired outcomes. The interface can be used in a number of ways, *viz.*:

a) Solutions can be optimised for a particular KPI (such as cost, energy savings and embodied carbon) by pressing minimise or maximise symbols beside the corresponding slider.

b) Constraints can be set for particular KPIs by moving the minimum or maximum sliders to desired levels.

Particular options can be selected meaning that they must be part of the solution *e.g.* the 67.8mm wall insulation option in Figure 5. Excluding options will also be available in future versions.

Thanks to the use of the MDD datastructure, these operations can be performed quickly and efficiently. As discussed before, the MDD is complete and correct, and thus the number of remaining configurations and their make-up are accurately reflected in these results.

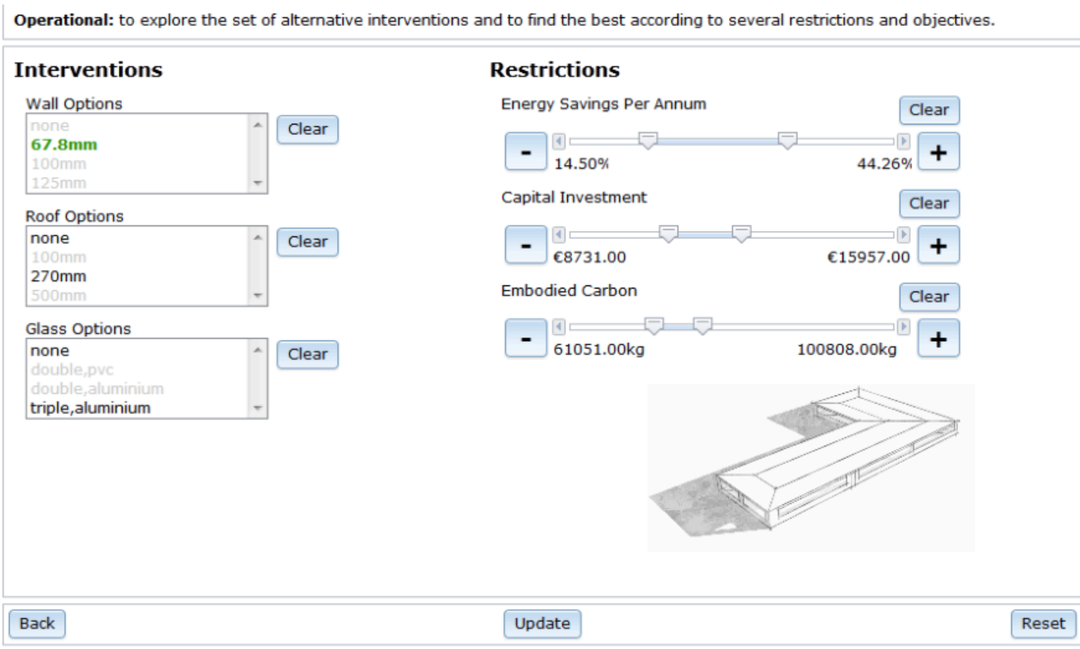

Figure 5. Screenshot of system illustrating user experience (UX) of selecting constraints and desired outcomes

DISCUSSION

CASE STUDY

A hypothetical office located in Cork, Ireland is used in this paper as a case study. It is a one-story L-shaped building of *ca.* 975m² with a flat roof. The baseline building has relatively poor energy performance (*ca.* 188 kWh/ m²/ yr). A number of potential energy retrofit options were considered for this building involving improvements to wall insulation, roof insulation and upgrading of window glazing. These options are listed in Tables 2-4.

Table 2
Possible upgrades to windows

No.	Description
0	No change
1	Double - 2x clear glass air insert, PVC frame
2	Double - 2x clear glass, Argon gas, Al frame
3	Triple - 2x clear glass, 1x glass (LoE coating), Argon gas, Al frame

Table 3
Possible upgrades to wall insulation

No	Description
0	No change
1	67.8mm fibreglass
2	100mm fibreglass
3	125mm fibreglass

Table 4
Possible upgrades to roof insulation

No	Description
0	No change
1	100mm fibreglass
2	270mm fibreglass
3	500mm fibreglass

Together with the option of not improving a particular aspect of the building (*i.e.* not changing a parameter), the above alternatives give rise to a total of 64 different configurations (4x4x4). The user input consists of a description only of the 9 possible interventions, however. The software automatically derives the scenarios in which a combination of interventions is used. Thus, the amount of manual work required is minimised. Each solution was run through EnergyPlus to derive estimates of the associated avoided energy consumption. While there may be a great many possible scenarios to evaluate, the problem falls in the class of so-called *trivially parallelisable* problems. Problems in this class can be straightforwardly solved using a cluster of CPUs. The reason for this is that each of the scenarios can be evaluated in isolation. For this case study, we used 4 cores (Intel Xeon E5430, 2.66GHz) to compute the results in less than 10 minutes.

In a typical building renovation where the potential number of interventions is much larger the final number of potential solution would be many times greater. However the approach described here is scalable and consideration of large number of solutions does not pose a challenge. While the computation of the outcomes of each of the scenarios might take some time (again, this can be easily capped by exploiting the parallelism as discussed before, and using*, e.g.* cloud computing facilities that provide a huge amount of computation power as needed). Once the configurations are evaluated, the MDD provides a scalable data structure that can be queried in linear time.

An MDD was generated from combinations of, and different parameters associated with, individual interventions along with associated KPIs. This MDD representing the 64 different solutions and their outcomes can be constructed within a second. The number of options for each intervention is not exhaustive, but is representative. This cuts down the size of the MDD and allows real time interaction. Remember, this approach can complement existing optimisation methods by providing a reduced initial search space within which the algorithms will find the exact detailed values for each intervention. The basic, uncollapsed, MDD contains 323 nodes and 384 edges. However, this can be collapsed down to 155 nodes (which is a reduction of over 50%) and 216 edges, by choosing the right order in which the interventions appear in the MDD. (A random test over 1000 different orderings show that on average, the resulting graph is 244 nodes, a 24% reduction).

The MDD was then interrogated exploring the trade-offs in order to find the optimum solution for a number of different scenarios, as described below.

Scenario 1. No restrictions

In order to understand the upper bound on performance without any cost or design constraints, the system was asked for the way to achieve the best performance.

This optimisation for energy savings or avoided consumption, with no constraints is obtained by selecting the ‘energy savings’ maximise button, the resultant solution comprises the combination of the improvement options with the largest amount of energy savings *viz.* 125 mm wall insulation; 500mm roof insulation and triple glazing, argon fill. The solution offers 60.61% energy savings per annum with an investment of €28,205 and represents 241,086 kg embodied carbon.

Figure 6: Optimisation for energy savings with no constraints

Scenario 2: Investment upper limit

In this scenario, investment is taken as an input constraint and capped at €15,000. The optimum configuration for reducing energy consumption is obtained by setting the rightmost slider of ‘capital investment’ to €15k, selecting update and choosing the ‘energy savings’ maximise button.

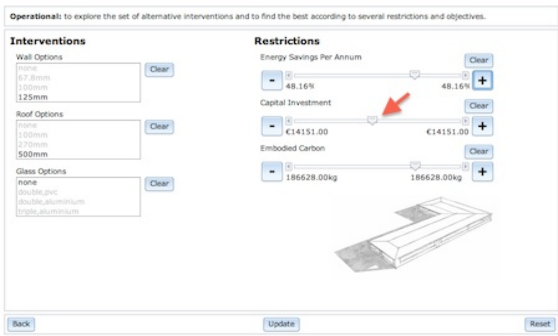

Figure 7: Optimisation for energy savings with maximum investment of €15,000

The resultant configuration involves upgrades to wall and insulation only: 125mm wall insulation and 500 mm roof insulation. This configuration offers a lower annual energy savings per annum of 48.16%, but lower embodied carbon (186,628 kg) and comes in under budget at €14,151.

Scenario 3: Embodied carbon upper limit

If the upper limit of embodied carbon is set at 40,000 kg, a number of potential options cannot be part of the solution, as they would breach the limit on embodied carbon. Of those options remaining the optimum solution for reducing energy consumption, comprises: 100mm roof insulation

Figure 8: Optimisation for energy savings with maximum embodied carbon of 40,000kg

This configuration results in annual energy savings per annum of 35.25%, but for a substantially lower embodied carbon (34,895 kg) and comes in a cost of just €5,365.

Scenario 4: Minimum improvement

If a minimum performance improvement is set to that equating with 40% energy savings per annum, when we optimise for minimum investment we get a configuration of 67.8mm wall insulation and 100mm roof insulation.

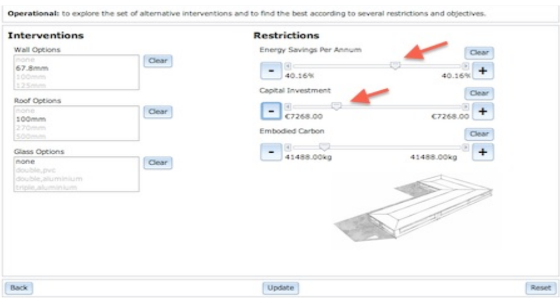

Figure 9: Optimisation for minimum investment with minimum energy savings of 40%

These improvements to the building offer 40.16% energy savings per annum for an investment of €7,268 and 41,488 kg embodied carbon.

Compromise and trade-off

As established above, it is not possible to achieve simultaneously the best KPI's given the real restrictions of finance and architect's preferences. A key attribute of this system is that it shows users immediately the impacts of choices at intermediate stages and thereby allowing them to be fully in control at all times.

Figure 10 below illustrates the feedback during the user interaction. Using our case study example, with the investment limited to €12,500 the option of triple glazing is not available as shown at (a). If we select wall insulation of 125mm, it can be seen that options for both roof insulation and window upgrading are reduced as shown at (b). While if 100mm roof insulation is selected there is not enough finance for upgrading the windows as shown at (c).

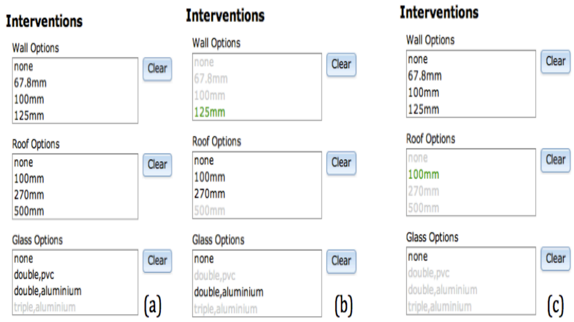

Figure 10: Visibility of trade-offs during user interaction

Another type of feedback provided by the system is through the sliders as shown in figure 11 below. In this example, the options for 100mm roof insulation was selected as a constraint – the range of all the KPIs immediately reduced as illustrated in change between the top and bottom images.

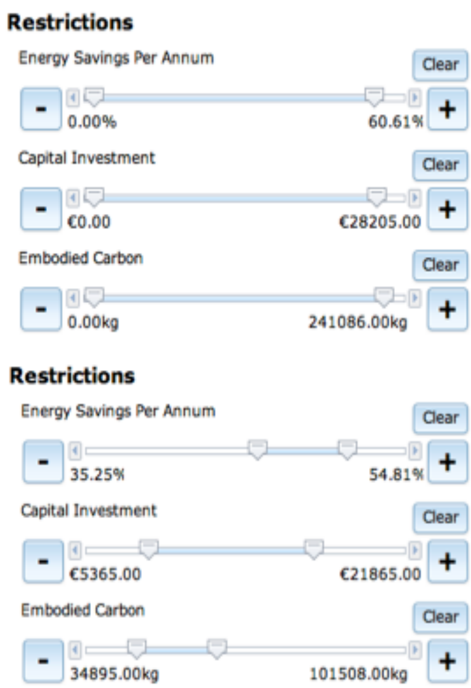

Figure 11: Feedback via slides during user interaction

CONCLUSION

A number of decision support features have been shown which are appropriate to the decision process the designer goes through. Mainly these are to, (1) indicate what is the set of interventions to achieve the best single KPI value, and (2) show the immediate impact on all other open choices relating to the building.

The MDD is a scalable datastructure, but does depend on there being lots of common interventions across all retrofit design – which is a reasonable assumption.

The approach puts the designer firmly in the driving seat, able to express their subjective choices but within a very objective framework. This approach indeed complements existing optimisation techniques. The latter can still be used afterwards, once the designers have narrowed down the feasible options. This in turn, because of the smaller search space, means that these algorithms will perform better.

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