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Optimum building energy retrofits under technical and economic uncertainty

A.M. Rysanek*, R. Choudhary

Department of Engineering, University of Cambridge, Cambridge CB2 1PZ, United Kingdom

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ABSTRACT

In a prior study, the authors showed that decomposing holistic, blackbox building energy models into discrete components can increase the computational efficiency of large-scale retrofit analysis. This paper presents an extension of that methodology to include an economic cost-benefit model. The entire framework now comprises an integrated modelling procedure for the simulation and optimisation of retrofit decisions for individual buildings. Potential decisions can range from the installation of demand-side measures to the replacement of energy supply systems and combinations therewithin. The classical decision theories of Wald, Savage, and Hurwicz are used to perform non-probabilistic optimisation under both technical and economic uncertainty. Such techniques, though simple in their handling of uncertainty, may elucidate robust decisions when the use of more intensive, probabilistic assessments of uncertainty is either infeasible or impractical.

1. Introduction

The building services industry has in recent years witnessed a resurgent public interest in building energy retrofits, largely due to a confluence of global economic drivers that emerged in the late 2000s. Whilst climate change mitigation might have been the 'top' priority in the previous decade,[1] the global recession and ensuing public debt crises seemed to hail the return of 'energy efficiency cost savings' as the popular rationale for refurbishing buildings [2,3]. However, much of this renewed political interest still contrasts with the reality, which has been well documented, that individual building owners still face a number of barriers to retrofit uptake [4,5]. This work particularly highlights the persistent information and risk gap between the policymakers, who promote new retrofit incentive schemes, and the individual energy consumers who must pay for them.

The specific point that needs to be underscored is that the *optimum* type of retrofit to perform on any particular building cannot be assuredly determined on the basis of a single macro-economic report or exogenous case study, nor can it usually be determined by expert judgement alone. As every building exhibits unique architectural, geographical, and operational characteristics, however nuanced, retrofit options must be rationally investigated for every individual building in a building stock. Specific investment decisions are made by energy consumers themselves and the engineers (or contractors) they hire from relevant trades, and therefore varying degrees of analysis are conducted. To this end, when the decision to invest in a particular retrofit depends on the specific cost/benefit of the work, one of the greatest tools available to professionals are computational building energy models (BEMs) – programs that provide the capacity to simulate building energy physics in detail. Indeed, since over three decades of research, development, and commercialisation, it has become standard practise to use BEMs for the design, specification, and evaluation of energy supply systems and energy-efficient demand measures in new building projects or large-scale renovations. Simulations using dynamic tools such as TRNSYS, EnergyPlus, or IESve, are most widely known, namely due to the tools' ability to capture – at small time steps – the salient physical interactions between energy supply systems and the built environment [6]. In this work, we discuss a number of issues faced when using conventional BEMs for optimal retrofit decision-making, and propose a holistic method of adapting BEMs to better suit these challenges.

1.1. Challenges for retrofit decision-making using simulation models

Though the terminology may differ regionally, building energy retrofits can be often classified into two types of endeavours: conventional and 'deep-energy' [7].

Similar to new building constructions, deep-energy retrofits are considered large-scale refurbishments that make significant alterations to a building's architectural design, componentry, and operations towards effecting major energy savings (upwards of 50%). Conventional retrofits are comparatively smaller in scale and

* Corresponding author. Tel.: +44 1223 748 595; fax: +44 1223 332 662.
E-mail address: amr63@cam.ac.uk (A.M. Rysanek).

[1] Procuring energy services for existing buildings accounts for roughly 40% of annual greenhouse gas emissions in OECD countries [1].

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cost. They focus primarily on replacing only one or a few technologies in a building, such as an ageing boiler or inefficient glazing, to achieve a modest reduction of energy consumption or greenhouse gas emissions (approximately 15–25%).

With a rational investor, in either type of project, the decision to replace or install multiple discrete technologies depends on the specific marginal benefit they each provide to *existing* building operations. As information on current energy costs and occupancy patterns is available, the success of retrofit projects can be directly measured against existing conditions. This presents such projects with a number of economic considerations that are additional to – though interacting with – the engineering objective of delivering services efficiently. Whether it is to meet self-instituted or regulatory energy reduction targets, or whether it is to meet external financing commitments, building operators can place onto retrofit projects very stringent constraints (such as capital, operation, and maintenance costs), objectives (such as payback periods and carbon emission targets), and investment time horizons (influenced by equipment life-cycles) related only to energy consumption.[2] We identify in this work three challenges that are faced when such problems are evaluated using building energy models.

The *first* challenge relates to a methodological gap between the current state-of-the-art in BEM optimisation and the conditions facing retrofit decisions as described above. Full recognition must be given to the fact that, energy *optimisation* using dynamic BEMs – although still infrequently applied to commercial projects – is a developed track in the field of building simulation. It is broadly characterised by the integration of known optimisation algorithms – such as generalised pattern searches or genetic algorithms – into building simulation software. The goal is to identify the ideal building form and/or energy system parameters for the minimisation of costs and/or ecological footprints [8–12]. However, in the same way as for commercial building energy models, the development of sophisticated whole building optimisation tools has tended to focus on parametric optimisation of design configurations in relation to operational energy costs. Factors such as investment value maximisation and risk mitigation under variable economic scenarios have typically fallen outside the realm of the building simulation domain, and have instead been evaluated under the remit of financial valuation studies [13,14].

This concentration on either economic or engineering matters may not be altogether useful for building retrofit assessments. Empirical evidence indicates that the implementation and success of retrofit projects may rely as much on accurately depicting economic conditions as it does on estimating the engineering performance of chosen energy efficiency measures [5,15,4].

Second, although the objective of any simulation approach to retrofit decisions may rest on determining only the necessary, optimum investment strategy, there is value in characterizing the wider decision search space from the outset. Whilst an optimisation model may answer to several criteria, such as the minimisation (or maximisation) of capital costs, investment value, or environmental impacts, there is always the potential for less-than-optimal choices to be made due to biases or prior preferences exhibited at the design- or decision-stages [16–18,4]. Klotz [16], who describes this in detail, presents some colloquial examples. For instance, in consulting negotiations, building operators could be sceptical of certain proposed technology solutions if they deviate too far from the status quo. In another instance, the use of standards (e.g., LEED) to set decision guidelines may constrain the selection of low-energy solutions in cases where the use of alternative targets (e.g., net-zero energy consumption) would be more effective. In our view, performing an exhaustive analysis of all feasible decisions is only one suggested way to improve the qualitative impact of a retrofit optimisation model's outputs. Doing so allows for immediate visualisation and discussion of the cost/benefit differences between optimal and non-optimal decisions [19], and makes it possible to consider multiple sets of objectives and constraints out of a single dataset.

Third, on top of modelling the interactions between engineering parameters and economic projections, there is a desire in retrofit analysis to characterise how investment options would fare if new technologies and controls would not perform as expected. Many reasons for this stem from practise. On the engineering front, for example, poor commissioning of retrofits may preclude any of new heating systems, façade modifications, or electricity demand measures from operating as efficiently as defined by specifications [20,21]. On the economic front, energy prices may fluctuate unfavourably, governments may reconsider technology subsidy/tariff schemes, and emerging technology costs may not reduce as much as expected [22,4]. The combined effects of these uncertain parameters can yield a significant decrease in the economic and environmental benefits of any one retrofit option, thus potentially affecting the overall direction that should be taken.

However, any detailed uncertainty quantification (UQ) using Monte Carlo – or similar – sampling of probabilistic inputs requires the capability to undertake large numbers of simulations. In the dynamic BEM environment, this is always a challenging proposition and wholly dependent on the number of inputs to be varied. It may be telling that, so far, UQ using dynamic BEMs has been used to evaluate individual classes of building systems – such as façades [23–25], energy supply systems [26,27], or occupant behavioural modes [28,29] – and rarely all in combination.

Whilst the challenges described above remain, in the following section we discuss some of the recent progress that has been made in adapting BEMs for retrofit assessments.

1.2. Current techniques for building design and retrofit optimisation using BEMs

In the previous section, we stated that a typical function of building design – or retrofit – optimisation projects is to evaluate a number of potential, *discrete* design configurations in the physical simulation environment. The particular challenge which has faced modellers is that conventional, dynamic BEMs do not natively feature the programmability or computational efficiency to do so with ease. In the available literature, this issue has been approached in three manners.

The first is arguably the most straight-forward, *brute-force*. The development of BeOPT and OptEPlus, both of which are front-end applications to EnergyPlus, are notable examples [30,31]. In both cases, developers decided that if dynamic BEMs are lacking in automatability and computational speed, then one needs only to create a third-party automation program and employ a larger computing cluster to perform discrete choice optimisation. This is a similar principle to that which guided many of the other optimisation studies cited earlier. The critique of these approaches, as are made in the publications below, is that the number of design variables is typically limited to a small set. The argument continues that, any increase in the number of computational runs – whether due to a larger set of design variables or the need to quantify uncertainties in outcomes – would render such models impractical for most applications outside of research.

The second manner has been to employ optimisation algorithms with simplified, quasi-steady-state models BEMs. Such models estimate the aggregate energy consumption metrics of a building over large time periods and are typically developed from linear, single-zone energy balance models [32]. By doing so, they can

[2] This is admittedly not always unique to retrofit projects; new building works can face similar considerations.

very quickly, and with minimal user input, assess large numbers of technology options [33–35]. Furthermore, given that existing data on a building's energy performance is available, model calibration can be applied to quantify physical parameter uncertainties and propagate them to uncertainty in the cost-benefit of retrofit measures [36,37]. One of the caveats facing such simplified BEMs, however, is that the relevance of their estimations can be limited to their inherently large time-step sizes – usually monthly iterations. They are generally unable to perform cost/benefit analyses of retrofit measures that are affected by either instantaneous demand – such as energy supply systems and advanced controls – or real-time energy pricing.

The third manner is to use high-fidelity surrogate (or meta-) models of dynamic BEM simulations to rapidly evaluate the technology decision space [38]. Metamodels of this sort attempt to capture the best of both methods above; they can undertake optimisation and probabilistic uncertainty analysis of dynamic building operations, but do so at a fraction of the overall computational cost.

However, the process of generating a dataset to regress a metamodel can be time consuming. In the case study of Eisenhower et al. [38], a greater number of BEM simulations were required than if a single set of objectives were optimised using a dynamic BEM directly. It may pose the question whether such metamodels can reduce the overall cost of retrofit decision-making, for a particular building, from start to finish. It also appears yet unclear, in the published methodology, whether such metamodels are suitable for non-parametric optimisation – the cases where decision variables are choices between technology measures rather than parameters of a chosen technology set.

Nevertheless, what the studies above indicate is that simulating building performance using dynamic BEMs remains the benchmark by which engineers investigate, in detail, the full range of building technology options that are available. There is little indication that this will change in the near-future.

2. Purpose of study

In Section 1.1, we identified three main challenges when using conventional BEMs for retrofit decision-making. This study sets out to illustrate an alternative methodology for analysis and optimisation of retrofit decisions using dynamic building energy models. The development of this work is based upon two methodological standpoints, which will be discussed further, and which the authors hope to be of value to the building simulation community:

1. The estimation of energy consumption using sequential models can be a means to reduce the computational expense of a more exhaustive characterisation of technology options. We have illustrated the development of the sequential models in Rysanek and Choudhary [39], and summarise it for our current readers in the introduction of Section 3.1.
2. The optimisation of retrofit options is multidisciplinary, and one may rarely be able to assume *all things being equal* in order to ignore salient economic or engineering parameters or their uncertainty. In Section 3 we present the multidisciplinary model, focusing on the description of the newly added economic assessment model. We present our methodology for uncertainty handling in Section 5, where we also propose that non-probabilistic decision rules can be usefully applied when one faces largely unknown economic scenarios.

3. Description of the engineering-economic model

3.1. Summary of the engineering model

The model used in this work represents a combined engineering-economic assessment model of building energy systems. At its core, it computes building energy demand using TRNSYS 17 [40]. However, a number of modifications have been made to the standard approach to building energy modelling using TRNSYS in order to improve the speed at which accurate performance estimations of numerous retrofit options are made. These modifications are described fully in Rysanek and Choudhary [39].

A useful analogy to the origin of these modifications is elicited through a Sankey energy diagram, though viewing it in reverse, as illustrated in Fig. 1. Sankey diagrams of this sort identify the relationship between building occupants, the services they need, and the energy consumption required to deliver them [41]. Though they make it clear that energy is delivered from primary resources to end-users, we understand that the starting point of *modelling* the energy flows in a Sankey diagram is to first characterise the demand-side conditions. This would suggest that, to estimate final

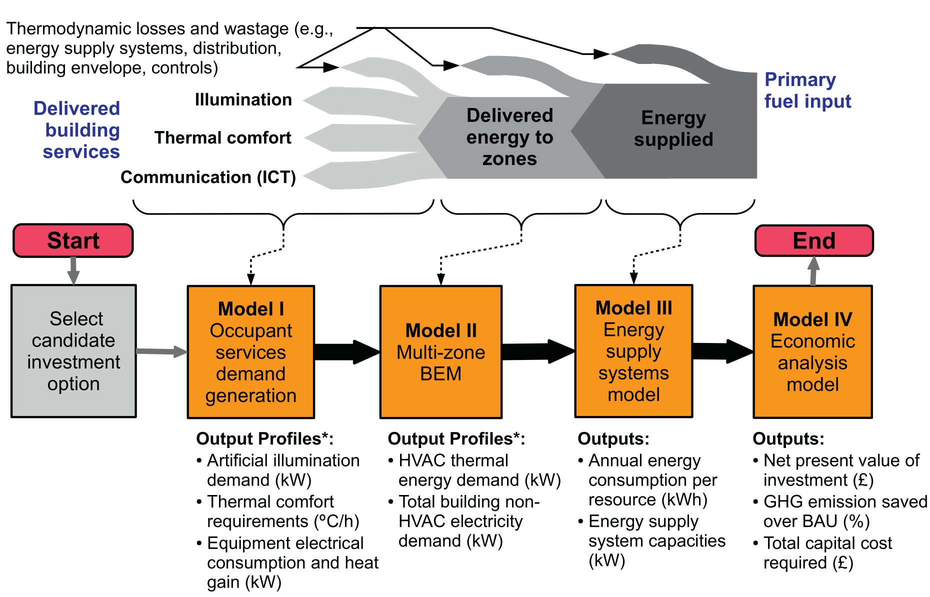

Fig. 1. Comparison of modelling approach to a Sankey energy flow diagram.

energy consumption, one would sequentially evaluate how services demand converts to end-use energy requirements, and how this in turn results in primary fuel usage. Those familiar with commercial BEM packages – some have been mentioned earlier – will observe that such a sequential process is not often explicitly provided. Normally, the entire process covered by the Sankey diagram is investigated using a single, integrated simulation platform. In other words, energy services, demand, and consumption are evaluated all at once even if one only wishes to investigate changes to individual system components (e.g., energy supply systems) from one case to another.

The technical undertaking behind this work has been to decouple this standard dynamic building energy modelling environment into discrete models for each step of the sequence above. We represent the first part of the sequence with an occupant services model (Model I), which generates transient demand profiles for each of thermal comfort, illumination, and equipment (heat gain and electricity) in respective units. These profiles become exogenous inputs to the building energy demand model (Model II), which then determines what amount of energy, namely for space conditioning and total electricity, must be delivered to the building zones. These new profiles are treated as the inputs to the separate energy supply systems model (Model III), which determines what amount of primary energy is required to deliver the heating, ventilation, and air conditioning (HVAC), and electrical loads.

Disassociating the BEM environment into discrete models proposes a series of benefits. Principally, it allows for changes in parameters of downstream models to be investigated without repeated simulations of upstream ones. For instance, if one wishes to evaluate two different types of energy supply systems for a given building, one needs to simulate end-use energy demand only once using an appropriate building physics model. This is an important attribute if one wishes assess multiple design options with minimal computational resources.

As stated above, the technical methodology behind these three models is described fully in Rysanek and Choudhary [39]. Their development was heavily influenced by, or adapted from, related works on stochastic behaviour modelling [42,43], post-occupancy or empirical evaluations of HVAC distribution systems [44,45], the CEN-ISO calculation standards [46], the modelling of energy supply systems using part-load efficiency profiles [47–49], and the component-based modelling structure of TRNSYS.

3.2. Possible retrofit measures

In developing the engineering model, the authors attempted to capture most salient types of energy-efficient and low-carbon retrofit measures, with a particular focus on European buildings. A list of possible retrofit measures is shown in Fig. 2. As is illustrated, a binary key identifies which retrofit measures are pre-selected for analysis, **k**. This key is required as input to both the engineering and economic sub-models.

Regarding the demand-reduction measures shown, the generalised descriptions are intentional. For example, by 'Improved lighting controls', this can mean a specific configuration that implements infra-red sensors to particular building zones, with manual controls in others. For 'Upgraded external glazing', this could entail installing either double- or triple-glazing panels with or without low-emissivity coatings. The specific selection of measures is determined on a case-by-case basis, but the model is structured to make this an easy step in the pre-processing stage.

That said, an important point to note is that measures covered by Models I and II are not optimised parametrically. If, for instance, a number of discrete glazing products are of interest, they must each be considered as an additional discrete integer in the technology key, **q**.

	Option key, **k**	Description
		Retrofit measure
Technology key, **q**	1	Energy-efficient lighting devices
	1	Improved lighting controls
	0	Energy-efficient appliances
	0	Energy-conscious occupant behaviour
	1	Upgraded external glazing
	0	Upgraded facade insulation
	1	Drought-proofing
	0	Improved external/internal shading devices
	1	Improved HVAC controls
	0	Insulated HVAC distribution network
	0	Electric-coil heating
	0	Non-condensing boiler
	1	Condensing boiler
	0	Biomass (pellets) boiler
	0	ASHP (central heating)
	0	ASHP (zone A/C)
	1	Small-scale CHP
	0	Solar PV
		Techno-economic scenario
Scenario key, **s**	1	Engineering performance regime
	0	Energy resource / fuel retail prices
	0	Resource / fuel decarbonization projections
	1	Technology costs
	1	Subsidies / Feed-in tarriffs
	0	Taxes / levies

Fig. 2. Retrofit measures and techno-economic scenarios covered by the model, and example of option selection keys. For retrofit measures, 1 = selected, 0 = not selected; for techno-economic scenarios, 1 = optimistic conditions, 0 = pessimistic conditions.

Some energy-efficient and low-carbon measures that are not presently assessed by the model include: thermal storage for space conditioning, solar domestic hot water, and ground source heat pumps (GSHPs). It is hoped to incorporate these measures into future evolutions of the model.

3.3. Inputs to the economic assessment model

The engineering models (Models I–III in Fig. 1) simulate the energy demand, consumption, and production of a particular

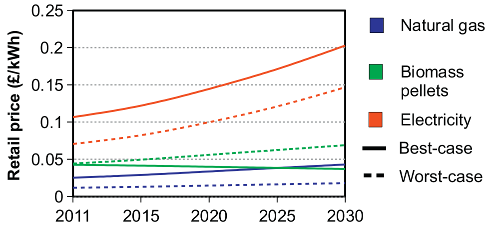

Fig. 3. Projected retail gas, electricity, and biomass (pellets) prices for UK non-domestic buildings. *Sources*: [51,52].

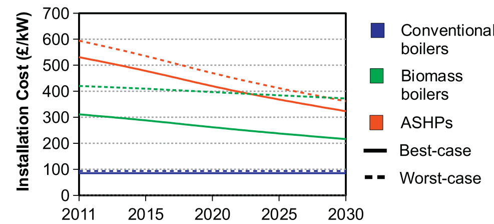

Fig. 4. Projected installation costs of energy supply systems. *Source*: [53].

building for an 8760-h year. In general, only two outputs from the engineering analysis are taken as inputs to the economic model: (1) the capacity (in kW) of installed energy supply systems, S_i, for every i-th system; and (2) the total energy consumed (or generated) per energy supply system and fuel/resource type, $E_{i,j}$, for every i-th system and j-th resource/fuel type. Possible values for the latter represent natural gas (g), grid electricity (e), biomass pellets (b), or solar photovoltaic energy (p).

Transient energy demand/consumption profiles are aggregated to annual values (kWh/annum). However, depending on the energy pricing schemes affecting the building, values may also be generated for fixed time periods. For example, if affected by day–night electricity pricing, grid electricity usage may be separated into total annual consumption during peak hours and off-peak hours.

3.4. Economic assessment model

The economic model is used to assess the cost/benefit of each possible retrofit strategy. As stated earlier, for every retrofit option only two variables are required: the total annual energy consumption per energy system (per fuel used over the accounting period) and the capacity (or size) of each technology installed. By using aggregate consumption figures, we are thus amortizing energy bills to relevant time periods – assuming any expenditures or revenues from electricity and fuel usage are costed in units of (£/kWh).[3]

The economic impact of a given strategy is modelled at each year of a user-defined timeline. The intervals at which it is possible for a new technology set to be chosen – and thus a new investment to be made – are user-defined. Feasibility constraints, also defined by a user, determine which technology combinations are possible. Also defined ex ante are the retrofit strategies which correspond to business-as-usual (BAU) scenarios. Therefore, the valuation of non-BAU investments is based on their value over and above to what would normally occur.

This work is presently concerned only with direct costs associated with building energy consumption and retrofit procurement. Other financial considerations, such as real estate asset value or tenant rent, are not considered in the current formulation. Thus, the presented methodology intends to target retrofit projects where financing of investments is sought through monetisation of energy savings, whether actual or virtual. This occurs particularly in cases where energy service companies (ESCOs) are employed [50].

3.4.1. Annual costs

For each year under simulation, the annual costs of a selected retrofit option are calculated. Defined in Eq. (1), the net annual cash flow X_y related to building energy expenditures covers energy bills (C_{bi}), equipment capital and maintenance costs (C_{CAP} and C_{OM}), revenues from any on-site energy generators (C_{ge}), grants and subsidies (C_{sb}), and government tariffs (C_{tx}), Negative values for X_y represent expenditures, positive values represent earnings.

$$X_y = C_{ge} + C_{gr} - C_{bi} - C_{CAP} - C_{OM} - C_{tx} - C_{pb} \tag{1}$$

The revenue made from selling electricity generated by N_{ge} types of installed energy supply systems, such as solar PV panels or micro-CHP, is defined in (2). The value is dependent on both the amount of electricity generated as well as the sale price, $P^*_{i,e}$. Energy bill payments are estimated similarly, see (3), whereby energy consumption values are combined with purchase prices $P_{i,j}$ for N_j number of fuel/resource types.

Government tariffs, G_t, of which there can be a total of N_t imposed, may be charged in either units of energy or greenhouse gas emissions. Eq. (4) shows tariffs imposed on energy consumption only; see (6) for the calculation of GHG emissions.

$$C_{ge} = \sum_{i=1}^{N_{ge}} E_{i,e} P^*_{i,e} \tag{2}$$

$$C_{bi} = \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} E_{i,j} P_{i,j} \tag{3}$$

$$C_{tx} = \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \sum_{t=1}^{N_t} E_{i,j} G_t \gamma_{j,t} \tag{4}$$

The estimation of capital costs, operating and maintenance (O&M) costs, and technology grants is done exogenously. For energy supply systems, future cost projections, based on installed system capacity, have been made available in literature. Examples of cost projections for energy prices and energy supply systems (e.g., boilers, air-source heat pumps, and micro-CHP systems) in the UK are provided in Figs. 3–5. For demand-side measures, anecdotal evidence is used to derive technology-specific costs when published data is not available.

For analysis of a retrofit strategy's overall cost/benefit, annual costs are compared to those that would be faced under BAU conditions, in the form of X_y^{rel} and defined by (5). BAU conditions describe the set of building technologies that would be installed without optimisation. It does not mean that BAU entails no retrofit is undertaken; life-cycle considerations may dictate that certain building technologies are replaced with newer versions.

$$X_y^{rel} = X_y - X_y^{BAU} \tag{5}$$

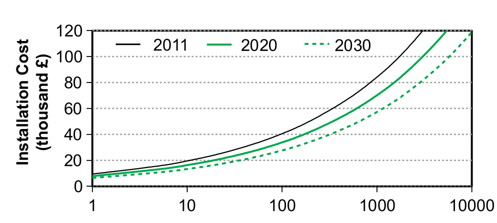

Fig. 5. Average installation cost projections of mini-CHP systems. *Sources*: [54,55].

[3] We use British pounds as currency throughout this paper; at time of writing 1 GBP = 1.58 USD.

3.4.2. GHG emissions savings

The GHG emissions intensity variable, γ_j in units of $kgCO_2/kWh$, is used to convert energy consumption of a particular fuel/resource into resultant GHG emissions. Values for γ_j may be either long-term constants or variable, depending on the particular fuel/resource. The carbon intensity of natural gas delivery and consumption, for instance, is not likely to deviate from the static value of 0.204 $kgCO_2/kWh$ it holds in the UK [56]. However, the emissions intensity of electricity is projected in the UK – as in many countries – to decrease over future years [57]. A description of values used for this study is provided in Table 2.

In terms of estimating the GHG emissions savings attributed to a retrofit, the metric used is an annual comparison of GHG emissions post-retrofit to BAU conditions. The former is calculated in (6), with relative emission savings calculated in (7).

$$GHG_y = \sum_{i=1}^{N_i}\sum_{j=1}^{N_j} E_{i,j}\gamma_j \tag{6}$$

$$GHG_y^{rel} = GHG_y^{BAU} - GHG_y \tag{7}$$

3.4.3. Present value of overall cost/benefits

Discounting of future costs/benefits to present values is one approach to quantifying the net merit of a particular retrofit investment option [58]. Calculating the net-present value of a retrofit strategy entails calculating the sum of discounted annual energy savings, each represented by X_y^{rel}. The general formula for discounting future costs to present values is shown in (8) for an arbitrary variable z at year y. An overbrace is used to symbolise discounted costs (e.g., $\bar{z}$ = present-value of z). The denominator value d is a simplification of $d = (1 + i)$, where i represents the discount rate of the investor.

$$\bar{z}_y = \frac{z_y}{d^y} \tag{8}$$

On the basis of (8), it follows that the NPV of a retrofit strategy is defined by (9) for an analysis of N_y number of years.

$$NPV = \sum_{y=1}^{N_y} \bar{X}_y^{rel} \tag{9}$$

Though not discounted, total GHG emission savings GHG_S over the project lifetime are calculated in the same manner as in (9).

$$GHG_S = \sum_{y=1}^{N_y} GHG_y^{rel} \tag{10}$$

The marginal abatement cost (MAC) of a particular option represents the inverse ratio of the retrofit's value over total emissions saved.

$$MAC = -\frac{NPV}{GHG_S} \tag{11}$$

The last metric of interest is the discounted payback period of the retrofit investment, $\bar{Y}_P$. This differs from simple payback by incorporating the time value of money, thus penalizing retrofits that provide returns on investment at a rate slower than what the investor could otherwise achieve.

An estimation for $\bar{Y}_P$ can be derived by first contracting the Taylor series in (9) and estimating the average annual revenue (e.g., energy cost savings) of each option, R_{avg}.

$$R_{avg} = \frac{d^{N_y}(1-d)(NPV + C_{CAP}^{rel})}{1-d^{N_y}} \tag{12}$$

$$\bar{Y}_P = -\frac{\ln[((1-d)(C_{CAP}^{rel})/R_{avg}) + 1]}{\ln d} \tag{13}$$

4. Optimisation problem formulation

The goal of the present model is to perform optimisation of retrofit options, and identify robust retrofit decisions. As the engineering-economic model is structured so as to undertake an exhaustive search of all feasible options and techno-economic scenarios, a user is able to investigate various combinations of optimisation criteria and constraints in post-processing. Thus, no formal optimisation algorithm is applied, and the problem is generally unconstrained.

In a general retrofit decision analysis, two particular optimisation criteria may be of most relevance:

1. *Marginal abatement cost vs. GHG emissions saved*: This scenario represents the popular comparison of investment value vs. environmental benefits. The marginal abatement cost of a retrofit strategy is the negative ratio between its NPV and total GHG emissions saved.
2. *Discounted payback period vs. required capital*: This scenario typifies the investor that is most concerned with long-term cost savings.

The optimisation pursued in this work is therefore multi-criteria, mainly of two objectives, X_1 and X_2, each respectively a primary and secondary objective. An objective's value is a function of the chosen retrofit option, **k**.

We recall from Fig. 2, however, that each option **k** is represented by a binary array **q**, which describes the chosen retrofit measures, and a scenario array **s**, which denotes the techno-economic conditions affecting the option. We use the notation $\mathbf{s}^*$ to denote an arbitrarily selected scenario out of a possible total of $\mathbf{N_s}$. We further use the terms $\mathbf{s}^0$ and $\mathbf{s}^1$ to define the globally pessimistic and optimistic scenarios respectively. These conditions will be discussed further in the following section.

It is also assumed, that from the outset of analysis, there exists an array $\mathbf{N_q}$ which lists all feasible combinations of measures (e.g., all feasible **q**). The designation of any technology-selection constraints is done a priori. Such constraints can represent conflicts between measures (where two or more measures cannot be installed simultaneously), or prerequisites (where one measure requires a set of others to be installed). As stated earlier, an example could be the case where one wishes to investigate the performance of various glazing product types. For such a problem, it would be sensible to constrain the selection key **q** accordingly in order to prevent overlap of multiple products.

Simulation of all feasible technology options is conducted in order to determine Pareto optimal decisions and define a characteristic Pareto frontier. Each feasible techno-economic scenario $\mathbf{N_s}$ is assessed independently.

$$\begin{aligned} \max:&\quad [X_1(\mathbf{q},\mathbf{s}), X_2(\mathbf{q},\mathbf{s})]^T \\ \text{foreach}:&\quad \mathbf{q} \in \mathbf{N_q} \\ \text{given}:&\quad \mathbf{s} = \mathbf{s}^* \end{aligned} \tag{14}$$

5. Decision-making under technical and economic uncertainty

We indicated earlier that one of the difficulties faced when incorporating uncertainty into holistic retrofit decision-making problems is the computational cost of performing probabilistic analysis with dynamic BEMs. One may understand this issue when the scale of the problem is reiterated. Earlier, Fig. 2 enumerated a set of salient retrofit technologies and techno-economic performance scenarios. We defined any discrete *retrofit option* through the key, **k**, which itself contained a discrete set of technology measures, **q**, and

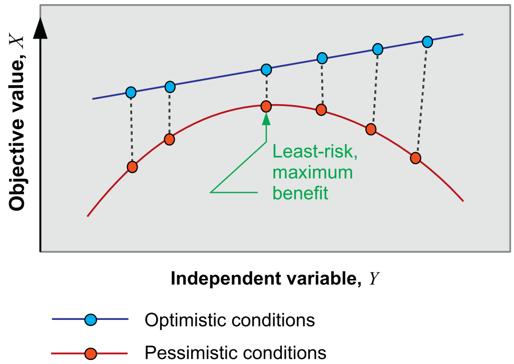

Fig. 6. Example of robust decision-making based on scenario modelling.

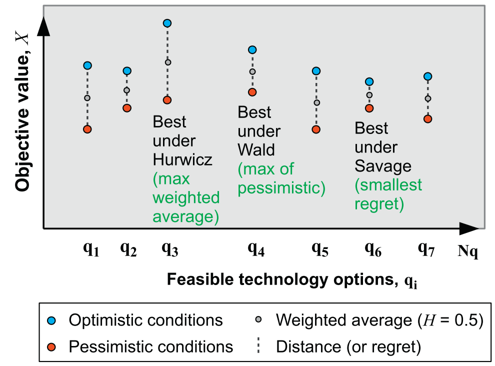

Fig. 7. Example of Hurwicz, Wald, and Savage regret criterion in the context of retrofit choice optimisation, notional case.

a discrete set of techno-economic scenario[4] options, **s**. If we would assume that any combination of the 18 technology measures and 6 economic scenarios shown would be feasible, the resulting case would be a decision space consisting of over 16 million possible options.[5]

Though this presents a decision-maker with a very large search space of possible outcomes, it also provides the possibility of determining good investment decisions under uncertainty, without explicitly quantifying the probability of individual scenarios occurring. Based on an exhaustive set of data, one may assume that there exists a finite number of retrofit options that are, in relation to all other alternatives, maximally beneficial and considerably more insensitive to a change in techno-economic scenario. A stylised example is shown in Fig. 6. In such a case, the best available choice for the decision-maker becomes obvious even though the probability of each scenario is not quantitatively known or defined. Discrete choice optimisation performed in such a manner is known classically as *robust decision-making*. More specifically, the ranking and selection of options based on the magnitude of change between optimal and non-optimal conditions is an application of the Savage minimax regret criterion [59].

Savage's criterion falls under the category of non-probabilistic decision rules, a number of which were developed and popularised by the seminal papers of Wald, Savage, and Hurwicz in the mid-20th century [60]. These classical techniques are applications of game theory in player vs. nature problems, where a decision-maker faces severe uncertainty regarding one or many exogenous scenarios.[6] Though they are deterministic techniques for assessing unknown information, they are in fact interpretations of Bayes' theorem. In other words, subjective expertise is combined with available knowledge in order to generate realistic scenarios unto which decision options are assessed. The work of Zmeureanu and Pasqualetto [62] is particularly highlighted, as they may have been the first to illustrate how these decision-making techniques could be applied to building retrofit problems.

[4] The term 'techno-economic scenario' is used in this paper to classify discrete regimes of retrofit performance. Each scenario **s** is identified by a set of assumed conditions on factors such as energy prices, government tariffs/subsidies, or the physical efficiency of retrofit measures. Each scenario option has a binary value representing either good/optimistic (1) or bad/pessimistic (0) conditions. Examples of some conditions were illustrated in Figs. 3–5, where projections of energy prices and energy supply system costs were depicted.

[5] $2^{18+6} = 16{,}777{,}216$.

[6] Info-gap decision theory may be a more well-known adaptation of these classical techniques, particularly in the engineering sector [61] However, this paper resigns itself to discussing and applying the more classical techniques of Wald, Savage, and Hurwicz as these remain the long-established alternatives to probabilistic characterisation of uncertainty.

The discussion of these approaches is continued further in the following section, and they are applied to the retrofit case study presented in Section 6.

5.1. Handling of uncertainty under Wald, Hurwicz, and Savage decision rules

Non-probabilistic decision rules, such as the ones introduced above, assume that a decision-maker has intrinsically little or no information regarding the uncertainty of exogenous scenarios. At best, there can be only a subjective view on whether a scenario is deemed optimistic or pessimistic. Though the mathematical formulation of these techniques have been elaborately structured in economic literature [63,60], their methodological application to real-world decision problems is simple to describe.

Let us assume a stylised example of a single-objective optimisation study, shown in Fig. 7. There, we plot a random distribution of options and their objective values, X, under optimistic and pessimistic scenarios.

Wald's criterion states that the best decision is that which provides the greatest value under globally pessimistic conditions. This is otherwise known as a *maximin* model of decision-making.

$$\begin{aligned} \max: &\quad [X(\mathbf{q}, \mathbf{s}^0)] \\ \text{foreach}: &\quad \mathbf{q} \in \mathbf{N_q} \end{aligned} \tag{15}$$

Hurwicz's criterion states that the best decision is one which balances expected returns under both pessimistic and optimistic conditions. Under Hurwicz decision-making, the process is to first calculate a weighted-average return for each option and then choose the maximum from these values, shown in (16). The weighting given to the averaging, the Hurwicz index H, describes the decision-maker's personal view on the likelihood of realised values nearing pessimistic or optimistic conditions. Hurwicz's criterion can be considered an adaptation of Wald's method, as Wald minimax decisions can be duplicated under Hurwicz rules.

$$\begin{aligned} \text{let}: &\quad X^{\mathrm{H}}(\mathbf{q}, H) = (1-H)X(\mathbf{q}, \mathbf{s}^0) + HX(\mathbf{q}, \mathbf{s}^1) \\ \max: &\quad [X^{\mathrm{H}}(\mathbf{q}, H)] \\ \text{foreach}: &\quad \mathbf{q} \in \mathbf{N_q} \end{aligned} \tag{16}$$

Savage's regret criterion, differing from the above methods, argues that decision-makers are not in pursuit of global maximum values in any scenario, but instead want to minimise the risk (or regret) if the realised scenario will be less than optimal. In other words, the objective is to find options that are most insensitive to a change in scenario in relation to other options.

$$\begin{aligned}
\text{let}:&\quad X^S(\mathbf{q}) = \frac{|X(\mathbf{q},\mathbf{s}^0) - X(\mathbf{q},\mathbf{s}^1)|}{\max[X(\mathbf{q},\mathbf{s}^0), X(\mathbf{q},\mathbf{s}^1)]}\\
\text{min}:&\quad [X^S(\mathbf{q})] \qquad (17)\\
\text{foreach}:&\quad \mathbf{q} \in \mathbf{N_q}
\end{aligned}$$

Though the approaches described above are effective at supporting decisions based on assumed best-case, or worst-case, economic conditions, it is clear that they will not provide an indication of any decision's sensitivity to an individual economic parameter such as energy prices or capital costs. At best, these rules will only identify the overall risk between two opposing scenarios (e.g., all-optimistic versus all-pessimistic).

A detailed sensitivity analysis would properly investigate the contributing effects of different economic parameters, such as energy prices or technology costs. However, the tenets of non-probabilistic decision-making suggest that this would not be necessary to produce robust recommendations. One attributes this again to the fact that, though optimistic and pessimistic economic projections can be defined within some accepted range,[7] the probability of any projection becoming reality is rarely known [64,65]. This remains one of the strongest arguments for non-probabilistic handling of uncertainty as per the criteria above: when the probability of an arbitrary scenario is not easily determinable, the robust decision will be one which is least-risky or least-affected by possible worst-case conditions [66,67].

In the following section, a case study is undertaken that illustrates the application of Wald, Hurwicz, and Savage's optimisation criteria to retrofit decision-making.

5.2. Characterisation of techno-economic scenarios from reference data

Though the treatment of uncertainty in this work is non-probabilistic, the data gathered for defining scenario options may or may not be derived from exogenous probability distributions. For instance, the energy price projections provided by the UK Department of Energy and Climate Change are categorised into low, central, and high scenarios without any statement on each scenario's probability. In comparison, the seminal work of Macdonald [25] quantifies the uncertainty of some physical variables, such as glazing or insulation *U*-values.

In converting probabilities between quantitative and qualitative terms, we follow the classification structure described in the Fourth Assessment Report (AR4) of the International Panel for Climate Change (IPCC) [68]. We subjectively assume that universally optimistic or pessimistic scenarios are either 'unlikely' or 'very unlikely' to occur. In accordance with the IPCC structure, such scenarios are expected to be realised between 10 and 33% of the time. This statistical correlation is used to generate plausible optimistic/pessimistic data points from probabilistic data.

For further clarification, in this paper we attribute engineering performance uncertainty only to the unknown effectiveness of commissioning, manufacturing, and installing new equipment. Following the approach of Heo et al. [36], the technical uncertainty attributed to a retrofit measure is represented by the variation of the measure's performance metric(s) – such as the *U*-value for a fabric retrofit – relative to its stated specification, upon installation. Thus, we do not examine long-term equipment degradation in this paper, nor do we look at the risk of technical faults, failures or other sudden shocks to equipment operations. This will require further investigation in future work.

[7] For instance, governments can provide estimations of future high and low energy price scenarios [51].

Table 1
Description of building, existing systems, and simulation model.

Actual building characteristics
Construction date: Between 1960 and 1961
Number of floors: Four
Total occupied floor area: 3265 m^2
Building type and zones: Mixed-use office building, with approximately 85 private office, 3 lecture rooms, one computer laboratory, a small cafeteria and library, meeting rooms and various IT/administrative areas.
Existing HVAC: Heating only, with centrally controlled LTHW radiator system. A high-efficiency non-condensing boiler was installed in the late 1990s.
Building fabric: Limited insulation throughout, as per original construction; single-pane metal-framed glazing without weather-stripping.
Lighting: T8 fluorescent lighting is installed throughout, with manual control only. Public corridor lighting is left on usually 24/7.
Occupancy habits: Occupants work typical weekday hours, with modest overtime. Approximately 50% of computing equipment is left switched on 24/7.
Special model characteristics
Building zones: 23 modelled zones, based on aggregation of building zones with similar operational and environmental conditions; influenced by 'façade-floor' zoning methodology defined by Corrado et al. [70]
Effect of local environment: Partial solar shading due to adjacent buildings is not considered. Transient weather projections provided by METEONORM [71]

6. Illustrative study

The case study used in this paper is a follow-on from the one initially presented in [39]. The subject is a mid-sized office building in Cambridge, United Kingdom, with minimal renovations since its construction in the early 1960s. It is indicative of a typical office building in the UK, where ~80% of such buildings remain naturally ventilated and the majority are classified with 'low' energy-efficiency ratings [69]. A description of the building and installed systems is provided in Table 1 and an illustration of the building and representative CAD model is shown in Fig. 8.

6.1. Retrofit conditions

The building owner is interested in determining the best-valued retrofit options that are under £150,000 in up-front costs. Optimum retrofit options must be also those that minimise risk due to technical and economic uncertainty, and treat GHG emissions mitigation as a secondary objective.

The investment time horizon is 10 years, starting in 2012. We assume no existing technology will reach end-of-life within this period, thus business-as-usual (BAU) conditions represent a do-nothing investment. We also assume that the installation of retrofit measures will not lead to any 'rebound' effect by building

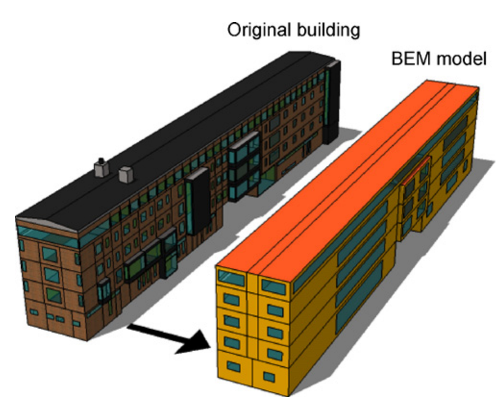

Fig. 8. Case study building and representative CAD model.

Table 2
Description of relevant economic scenario options.

Scenario option	Instrument	Optimistic conditions	Pessimistic conditions
Government tariffs	Carbon reduction commitment (CRC) levy[a]	CRC tariffs will increase linearly from £12/ton-CO_2 to £21/ton-CO_2 between 2012 and 2020[b]	Constant at £12/ton-CO_2
Government subsidies	Feed-in tariffs (FiTs)[c]	Solar PV – £0.33/kWh-generated	Same as optimistic
	Renewable Heat Incentive (RHI)[d]	Biomass – £0.05/kWth for first 15% of annual output, £0.02/kWth afterwards	Same as optimistic
	Enhanced Capital Allowance (ECA)[e]	25% of energy supply system investment costs can be written off as a tax credit	Same as optimistic
Carbon intensity	Electricity grid	UK electricity decarbonises linearly from 0.43 kgCO_2/kWh to 0.275 kgCO_2/kWh between 2012 and 2022[f]	Constant at 0.43 kgCO_2/kWh
	Biomass pellets	0.025 kgCO_2/kWh attributed to UK best practise of processing, transport, harvesting, and cultivation[g]	0.130 kgCO_2/kWh due to worst practise

[a] See http://www.decc.gov.uk/en/content/cms/emissions/crc_efficiency/crc_efficiency.aspx.
[b] The uncertainty of the CRC scheme is attributed to whether the levy will remain constant over future years, or whether it will be matched with the EU Emissions Trading Scheme (EU ETS) carbon price – itself an unknown variable. The European Commission has suggested an upper EU ETS price of £21/ton-CO_2 by 2020 [74].
[c] See http://www.fitariffs.co.uk/.
[d] See http://www.rhincentive.co.uk/.
[e] See http://etl.decc.gov.uk/.
[f] Taken from [57].
[g] Taken from [75].

occupants.[8] This is attributed only to this case study, which reflects a non-domestic commercial building. As discussed by Sorrell et al. [73] and Gillingham et al. [17], commercial buildings feature two conditions that contribute towards minimizing any potential rebound. First, energy costs remain a considerably small portion of total operating expenditures, thereby reducing the relative impact of energy savings on operational decisions. Second, building occupants are not typically responsible for energy costs and are thus not incentivised to demand for more or less services upon a change in the cost of energy procurement.

6.1.1. Techno-economic scenarios

The types of scenario options that are assessed were shown earlier in Fig. 2. A mix of reference literature and heuristic information provided the relevant 'optimistic' and 'pessimistic' data for each option. Figs. 4 and 5 earlier showed reference cost projections of various energy supply systems. Fig. 3 also illustrated reference cost projections of delivered energy resources and fuels. We refer to Table 2 regarding the optimistic and pessimistic conditions facing other triggers, such as government tariffs. Section 6.1.2 describes further capital cost and technical performance data.

Regarding the terminology of 'best-case'/optimistic or 'worst-case'/pessimistic scenarios used in this work, we reiterate that the classification of information into either category is based on the assumed correlation between a scenario's values and the retrofit's favourability. For example, it is assumed that when no retrofit is undertaken, the best-case scenario for a utility bill payer is to experience low energy prices in the future. However, when a retrofit *is* undertaken, this becomes the worst-case scenario. As the intention of a retrofit is to maximise energy cost savings with respect to BAU (e.g., no retrofit), persistently low energy prices will reduce the realised cost savings of any retrofit undertaken and lengthen its true payback period. Therefore, treating energy prices as low from the outset of analysis is the least-risky – or worst-case – approach to a selecting an ideal retrofit option, particularly if financing of the project is to be explicitly managed. This analogy summarises the approach taken to characterizing scenarios as optimistic or pessimistic.

[8] As defined in Sorrell and Dimitropoulos [72], the rebound effect occurs when building occupants react to a decrease in the cost of energy services with an increase to their demand for them.

6.1.2. Feasible retrofit measures

A set of possible retrofit measures has been defined ex ante. These include the following energy supply systems: high-efficiency non-condensing boilers (currently installed), condensing boilers, biomass pellets boilers, mini CHP systems, and air-to-water heat pumps for central heating. The engineering performance of energy supply systems under 'optimistic' conditions is determined by the nominal part-load efficiency curves set out in [39]. Under 'pessimistic' conditions, we assume the working efficiency of any energy supply system is 15% below nominal. The exception to this rule is when modelling the BAU system, which is assumed nominal in both pessimistic and optimistic scenarios. Thus, the purpose of reducing system efficiency under pessimistic conditions is not to simulate system performance degradation or operational faults, but instead to illustrate the effect of poor commissioning and poor system design after the initial stage of investment [76].

Candidate demand-side measures are listed in Table 3. The table also describes the salient physical input variables, their differences between optimistic and pessimistic technology performance scenarios, and their estimated costs. Investment capital costs are inclusive of procurement, transportation, and installation.

6.1.3. Constraints

Apart from the aforementioned capital constraint (£150,000), we allow for all feasible technology options and scenarios to be assessed, with one primary exception. It is assumed that the building will have only one type of energy supply system installed, with or without CHP. Thus, we do not allow for the combination of multiple types of boilers and heat pumps.

6.2. Results

An exhaustive simulation of all feasible technology choices yields 6144 discrete technology options per techno-economic scenario. Fig. 9 shows scatter plots of results under all-optimistic conditions. The purpose of the scatter plot is only to illustrate the overall variation in cost/benefit that occurs between various types of retrofit measures.

To understand which demand-side measures could achieve this requires deeper analysis into the model's results, as will be done in the following section.

Table 3
Description of possible demand-side retrofit measures.

Short name	Description	Salient performance metric[a]				Investment cost[b]	
		Variable	BAU	Optimistic	Pessimistic	Optimistic	Pessimistic
Draught-proof	Install weather stripping where needed	Building infiltration rate	0.55 ACH	0.45 ACH	0.50 ACH	£5000	£10,000
Roof	Install new roof	Roof *U*-value	2.8 W/m^2 K	1 W/m^2 K	1 W/m^2 K	£70,000	£81,000
Glazing	Install high solar-heat gain double glazing	Glazing *U*-value	5.6 W/m^2 K	1 W/m^2 K	1 W/m^2 K	£119,000	£151,000
T8–T5	Convert T8 lighting fixtures to T5 ballasts	Lighting energy intensity	100 W/lux	80 W/lux	90 W/lux	£12,000	£15,000
Voltage	Install voltage optimiser	Transient electricity demand	–	−7%	−4%	£10,000	£15,000
PIR	Install PIR sensors in public areas	Embedded in stochastic demand model; not varied between optimistic and pessimistic conditions				£3000	£5000
eTRVs	Install electronic thermostatic radiator valves	Detailed in [39]; not varied between optimistic and pessimistic conditions				£13,000	£18,000

[a] Other metrics may also be affected; values shown are for guidance. Relevant data sources for uncertainty forecasting: [25,36].
[b] Some data found heuristically or via web searches, otherwise from [77].

6.2.1. *The effect of techno-economic uncertainty*

Fig. 10 offers a better decomposition of results, providing insight into the effects of techno-economic uncertainty. The figures were devised by first characterizing the Pareto frontier of options under all-optimistic conditions. This was done for two cases: NPV vs. GHG emissions mitigated, and NPV vs. investment capital cost. In the first case, NPV-maximizing options were selected at intervals of 20% GHG emissions mitigated. In the second case, options were selected at intervals of £50,000. The figure illustrates the degree of regret that one faces as individual economic scenario options change and the underlying investment conditions become more pessimistic.

6.2.2. *Application of non-probabilistic decision rules*

Apart from the rather qualitative method of judging the economic risk of retrofit options, as shown in Fig. 10, one can specifically quantify and rank measures based on the robust decision criteria defined earlier in this paper. Three separate decision rules were identified: Wald's criterion (maximises value under pessimistic conditions), Savage's regret criterion (minimises total possible regret), and Hurwicz's criterion (maximises average-weighted benefit). Ranking of options under these metrics can be compared against each other, and can also be compared to the case of decision-making under notional conditions only, where one would arbitrarily select all-optimistic techno-economic scenarios. The top five candidate options under each criteria are highlighted in green in Table 4. Each option has been ranked based on NPV maximisation only, from highest (Rank = 1) to lowest (Rank = 6144).

7. Discussion

Fig. 9 illustrates the overall search space, and shows both the general cost and GHG-mitigation effectiveness of particular sets of retrofits. Demand-side measures (DSMs) seem to be most cost-effective and offer GHG mitigation potentials in the order of 10–40%. Combining DSMs with a gas-fired CHP system could yield an additional 15% of GHG mitigation potential, though the investment value would be reduced. Such observations can at least be made in the abstract. One interesting observation, however, is the vertical alignment of all measures that include biomass boilers. This indicates how non-electrical DSMs cease to influence GHG emissions but instead influence the long-term marginal abatement cost of biomass deployment. A greater penetration of DSMs will reduce overall HVAC demand – thus reducing the biomass fuel requirements and system capacity.

The colour-based categorisation of the scatter plots in Fig. 9 into types of energy supply systems could also foster discussion into

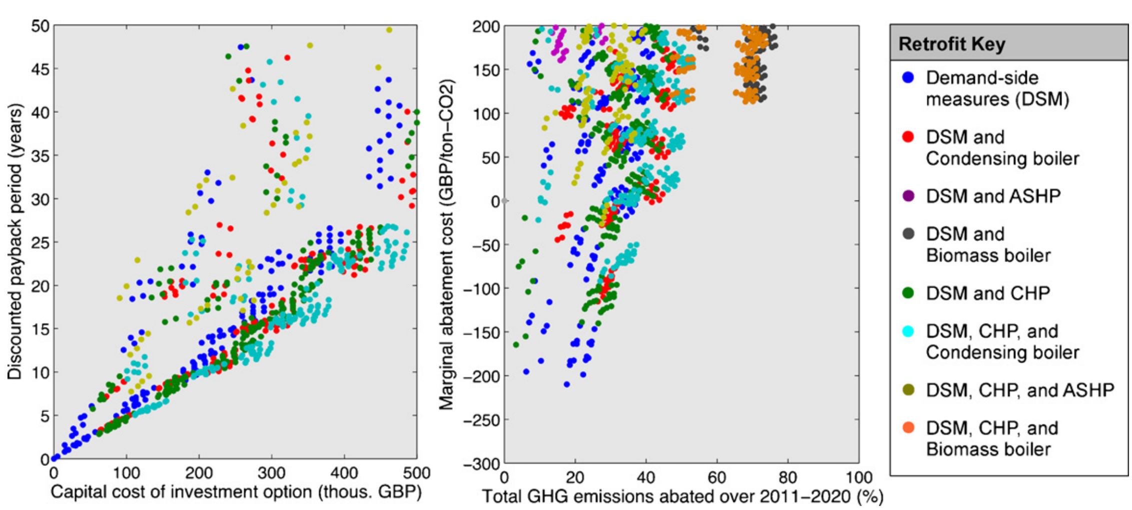

Fig. 9. Scatter plots of simulation results. Left: discount payback period vs. Investment capital costs. Right: marginal abatement cost vs. total GHG emissions abated.

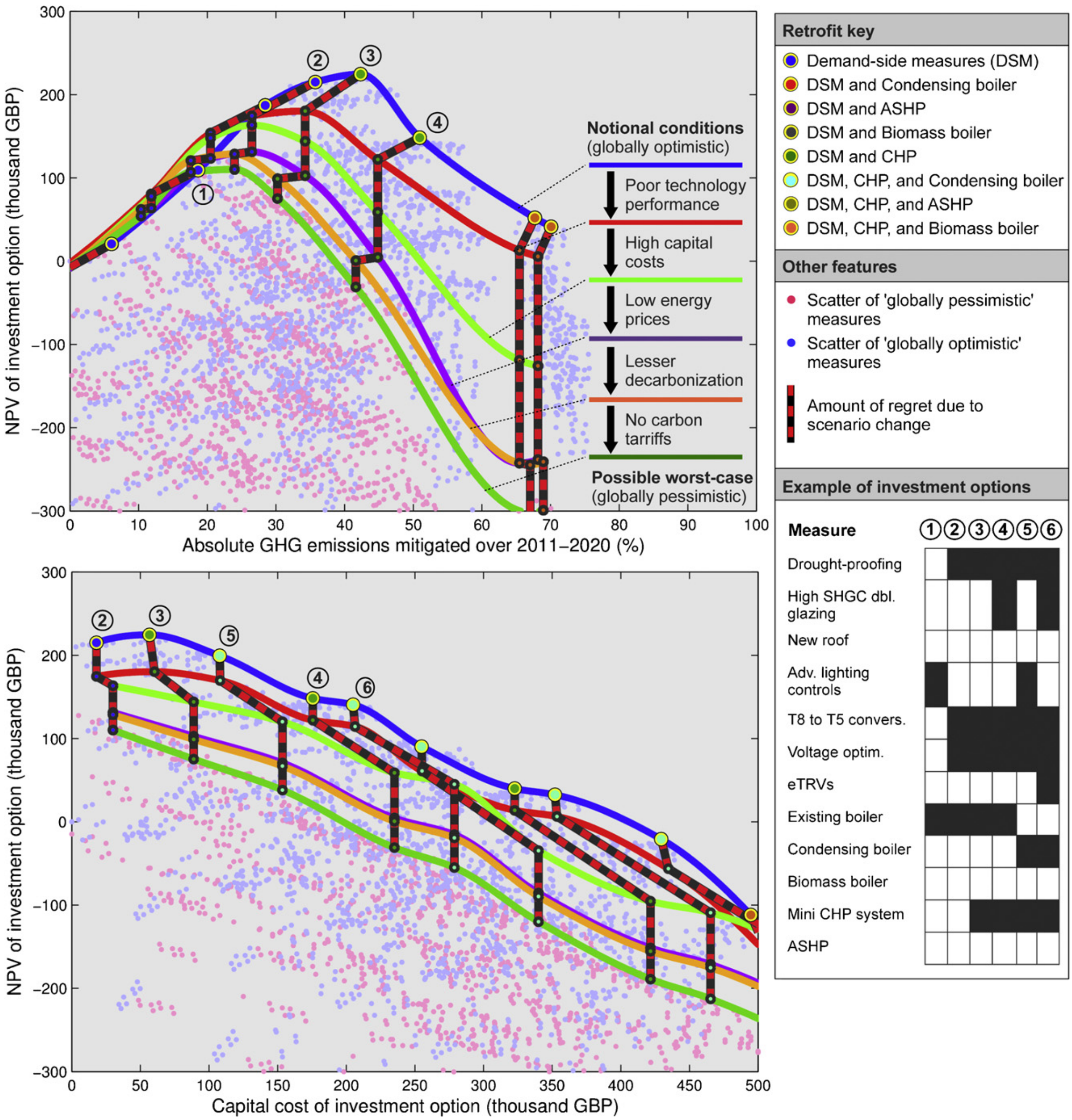

Fig. 10. Cumulative effect of uncertain parameters on ‘optimum’ options.

how GHG emissions abatement costs are assessed for individual buildings. For example, in the UK, as may be elsewhere, it is understood that retrofitting a typical building[9] with biomass boilers or air-source heat pumps (ASHPs) is an expensive endeavour [78]; the investment cost can be very high compared to annual energy cost and emissions savings. However, Fig. 9 shows the value of coupling investments in expensive energy supply systems with demand-side measures in order to effect high GHG abatement potential and low abatement costs overall.

Fig. 10 goes further to show the effect of uncertainty on actual retrofit option value. From the figure, it is not particularly surprising that the options which are most beneficial and risk-hedged are those consisting primarily of cheap DSMs. These have been long-considered the ‘low-hanging fruit’ of building retrofits in the UK [58]. The results are more interesting if one wishes to trade some investment value for increased GHG mitigation. For this particular building, it would seem that combining demand-side measures with a condensing boiler and mini CHP system would be the most cost-effective means to maximise GHG emissions abatement in the medium-term.

What is most telling from Fig. 10 is the effect of technical performance uncertainty when compared to the uncertainty attributed to economic variables. It would seem that, though engineering performance uncertainty is not trivial, it appears considerably less impacting on investment value than the effect of uncertain economic conditions. This is an important observation, not only for

[9] In this case, an ageing building with space-heating only, served by a hot water radiator network and gas boiler.

Table 4
Ranking of best options under non-probabilistic decision rules (out of 6144 options).

	Selected measures: Drought-proofing	Selected measures: PIR lighting controls	Selected measures: T8 to T5 conversion	Selected measures: Voltage optimisation	Selected measures: Existing boiler	Selected measures: CHP	Ranking: **Conventional** (notional conditions)	Ranking: Wald	Ranking: Savage	Ranking: Hurwicz	**NPV** (thousand £)	**Discounted Payback Period** (years)	**Capital Cost** (thousand £)	**GHG Emissions Mitigated** (% between 2011-2022)
Top 5 Notional conditions	■		■	■	■	■	1	33	39	15	93 - 225	1.6 - 4.2	57 - 89	30 - 42
			■	■	■	■	2	25	26	12	101 - 222	1.5 - 3.7	52 - 79	30 - 41
	■	■	■		■	■	3	18	19	10	108 - 220	1.7 - 3.7	59 - 84	31 - 42
	■	■	■	■	■	■	4	28	35	18	97 - 218	1.9 - 4.3	69 - 99	32 - 43
		■	■		■	■	5	11	12	8	116 - 218	1.6 - 3.2	54 - 74	30 - 40
Top 5 Under Wald, Savage, and Hurwicz			■		■		16	1	1	1	141 - 210	0.1 - 0.3	3 - 5	22 - 32
		■	■		■		15	2	2	2	135 - 210	0.5 - 1.0	15 - 20	24 - 34
	■		■		■		12	3	4	3	133 - 213	0.3 - 0.8	8 - 15	23 - 34
			■	■	■		13	4	3	4	132 - 212	0.4 - 1.0	13 - 20	23 - 34
	■	■	■		■		10	5	7	5	128 - 213	0.7 - 1.5	20 - 30	24 - 36
		■			■	■	11	10	5	8	120 - 200	1.5 - 2.8	48 - 61	26 - 34

practical applications, but for research as well. Though the retrofit optimisation problem certainly requires the expertise of an engineer, it may not be realistic to pursue any decision optimisation exercise that ignores the salient economic unknowns – or overly simplifies them.

Regarding the non-probabilistic decision criteria applied and shown in Table 4, a correlation seems evident between all decision rules applied. It's observed that those options which fare best under all-pessimistic conditions tend to also be the options which provide the least amount of regret. However, in light of this study only examining one case study building, no general rules should be drawn from this, though it may not be surprising to see this observation repeated for other building types. Altogether, the decisions rules – by explicitly incorporating pessimistic economic projections – can isolate those retrofit options which are better hedged against risk. For this particular building, however, there may be some semantics in this claim. All of the options presented in Table 4 provide relatively low payback periods and all fall within the capital constraint of £150,000. Thus, the uptake of a specific option may still largely depend on the subjective preference of an investor – one who wishes to negotiate between specific values of investment benefit, risk, and cost.

In any case, the following decision recommendations can be made for this particular building. Were the decision-maker to favour a very small payback period, the installation of T8–T5 lighting conversion would be the cheapest means to make energy cost savings, with additional energy efficiency measures offering little marginal benefit. However, were the decision-maker to be slightly more ambitious at the investment-stage, coupling select demand-side measures with a small-scale CHP system would provide additional GHG emissions savings with no significant impact on investment payback.

8. Conclusions

8.1. On the application of non-probabilistic decision rules to retrofit problems

The application of classical decision criteria, as presented in this paper, has been to illustrate the usefulness of non-probabilistic handling of uncertainty in a certain category of optimisation problems. We have attempted to show that such an approach can be useful for scenario modelling in the case of building retrofits, which exhibit a large number of feasible technology options and highly uncertain economic futures. Decision criteria based on game theory may elicit retrofit recommendations that are equally robust, and perhaps quicker to identify than a fully probabilistic analysis. The observation that future economic uncertainty might overshadow technical performance uncertainty is also important, as uncertainty in the former cannot be as easily defined probabilistically as the latter.

8.2. Relevance of the present model to real-world contexts

Despite the discussion of building retrofit problems provided in this work, we understand – as many others have in practise and research – that retrofit projects should not always be approached with a single analytical framework or assessment strategy. Though building energy models can be very capable tools, some retrofit projects will succeed primarily due to the expert insight of practitioners regardless of any detailed simulation that could be undertaken.

However, detailed simulations are often very useful, if not the only means by which we can quantify the cost-benefit or retrofit decisions in complex cases. The potential economic and environmental benefits of a small-scale CHP system, as just one example, depends heavily on a building's transient electricity and HVAC loads. These loads can be affected, for better or worse, by the installation of particular demand-reduction measures (e.g., fabric upgrades or lighting improvements), each having specific transient impacts on energy demand. It is not so much a question, for such a problem, whether detailed simulation of multiple retrofit options would be beneficial. Instead, it is a question of how costly would it be to generate relevant simulation data. In this work, we have proposed a methodology by which higher-fidelity simulations of possible decisions could be performed, without a significant incursion on available user or computational resources.

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