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Electricity supply industry modelling for multiple objectives under demand growth uncertainty

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Abstract

Appropriate energy–environment–economic (E3) modelling provides key information for policy makers in the electricity supply industry (ESI) faced with navigating a sustainable development path. Key challenges include engaging with stakeholder values and preferences, and exploring trade-offs between competing objectives in the face of underlying uncertainty. As a case study we represent the South African ESI using a partial equilibrium E3 modelling approach, and extend the approach to include multiple objectives under selected future uncertainties. This extension is achieved by assigning cost penalties to non-cost attributes to force the model's least-cost objective function to better satisfy non-cost criteria. This paper incorporates aspects of flexibility to demand growth uncertainty into each future expansion alternative by introducing stochastic programming with recourse into the model. Technology lead times are taken into account by the inclusion of a decision node along the time horizon where aspects of real options theory are considered within the planning process. Hedging in the recourse programming is automatically translated from being purely financial, to include the other attributes that the cost penalties represent. From a retrospective analysis of the cost penalties, the correct market signals, can be derived to meet policy goal, with due regard to demand uncertainty.

Keywords: Electricity supply industry modelling; Sustainability; Uncertainty; Multi-objective optimisation; Stochastic programming

1. Introduction

Electricity supply industry (ESI) modelling is a challenging task due to diversity of the supply side technology options available (influencing model size and complexity), the temporal evolution of parameters over medium to long-term time horizons, the non-linear nature of the systems under consideration, environmental and social arguments, as well as aspects of uncertainty in all realms of the modelling process. More recently, increasing deregulation of power markets has added to the uncertainty and has necessitated new methodologies and models to better understand the systems at hand [1–3].

ESI modelling methodology can be split into two phases: a primary step is the generation phase, where solutions, i.e. combinations of supply options, are generated in an energy systems modelling framework. A subsequent selection phase identifies preferred alternatives from within the set generated, based on policy maker and stakeholder preferences and value judgements. Both of these phases can be explored against a set of policy objectives, and both contain inherent uncertainties which relate to aspects of model definition, as well as valuation arguments.

The aim of this paper is to outline a methodology for the generation of solutions within an ESI modelling framework that considers multiple objectives, and includes aspects of flexibility to demand growth uncertainty into each solution. As such, we limit the scope of this paper to the generation of ESI scenarios only, and illustrate this approach for the South African ESI. Alternative selection

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and robustness analysis are addressed in a parallel paper dedicated purely to these issues [4].

2. Background

Large linear programming models have been used extensively over several decades to address ESI modelling [5–7]. Modelling with single objective functions has been a powerful tool in optimising power station expansion under specific environmental constraints, as well as for examining the economic feasibility of new options in the energy market. This type of analysis, done in partial equilibrium[1] frameworks, has provided policy makers with the "perfect market"[2] response to future scenarios that are valid for both regulated, centrally planned power markets, as well as for efficient fully deregulated markets. Although this type of modelling has enjoyed some success for integrated resource planning in the past, resource planning today has become a far more complex task [6]. What such an approach fails to deliver is explicit consideration of trade-offs between different objectives and the need to address uncertainty in the modelling process.

That said, this type of analysis and approach are familiar to many energy market analysts, and continue to form the basis of ESI planning in many instances. We argue that there is merit in exploring to what extent the "single objective least-cost" approach in partial equilibrium frameworks can be augmented to include other objectives and specific forms of uncertainty analysis to deliver more valuable outcomes from an energy modelling exercise. To place this proposal in context, a brief summary of some related approaches to ESI modelling considering multiple objectives and uncertainty is provided in the following section.

2.1. Considering multiple objectives

There are numerous methods that can be used to locate efficient or non-dominated[3] solutions to multiple objective linear programming (MOLP) models, see [8,9]. Some of the methods that have been used in energy planning are discussed below.

One approach is to analyse the trade-offs through a common objective, usually being cost, by assigning cost benefits or penalties to each of the major non-cost criteria. A sensitivity analysis performed on these parameters helps establish their individual effects on the overall cost. This method has been used in particular energy market analyses by permuting arbitrary "emission taxes" to generate efficient solutions for MOLP models with the aim of providing decision makers with a trade-off situation between cost and CO_2 emissions e.g. [10,11]. Although much work has been done to quantify the damage to both human health and the environment e.g. [12,13], when used in this form, the "emission taxes" do not imply to represent the actual cost to society resulting from the generation of electricity, but are merely used as parameters to force a model to generate solutions in relation to multiple objectives. This said, "taxes" used to generate preferred solutions may find value in providing policy makers with appropriate market signals to influence market behaviour.

Another approach is to re-cast all but one objective functions as a set of constraints operating on the remaining objective function. Examples of this are common in the process engineering literature—see, e.g. the *e*-constraint method, described, amongst others, by [9]. The range of constraints is explored systematically to generate a representation of the non-dominated solution space. In energy modelling, environmental objectives are typically re-cast as a set of emission, pollution or temperature (for climate change models) constraints, informed often by regulatory regimes e.g. [5,14,15].

A third approach is to evaluate the objective functions separately and to explore the solution space using weighted sums of the individual objective functions or by measuring the composite distance from an "ideal" or reference point. This involves interactive participation with stakeholders in the definition of the weights or goals until a satisfactory solution has been reached for the case of a single solution or a permutation of weights or goals to generate a representation of the non-dominated solution space. In the latter case, the weights or goals would effectively be used as generating parameters rather than being "true" weights representing preferences. Examples of interactive procedures include reference point methods such as goal programming [16] and achievement functions, see [17,18], the STEM method [19] and the interactive weighted Tchebycheff approach [20,21]. Applications of interactive methods in energy planning include [22–24].

2.2. Considering uncertainty and multiple objectives

Relatively few studies have undertaken the challenge of solving power expansion optimisation problems for a market faced with uncertainty, when there is an explicit desire to accommodate multiple objectives within the decision framework. Studies into this area generally propose methodology tailored to specific (and limited) applications [25,26]. It is challenging to extend such approaches to much larger, dynamic long-term analyses

[1] Partial equilibrium frameworks represent part of the overall economy (i.e. the energy sector) and have the properties that the prices and quantities of fuels and other commodities will be such that supply will meet demand exactly, in each time period, and further that total economic surplus will be maximised (or the total discounted cost minimised) over the time horizon.

[2] Note, however, that for modelling the response of an individual utility to investment planning decisions within a multi-player market, other approaches may be more appropriate (e.g. system dynamics, agent-based modelling or game theory).

[3] An efficient or non-dominated solution can be defined as a solution where a single attribute cannot be improved upon without sacrifice in another of its attributes.

because of the exponential increase of complexity that arises with larger models and the computational burden related to this. Another issue arising from including multiple objectives into the problem coupled with uncertainty is the overwhelming amount of information generated. This could present a substantial challenge for decision makers.

Uncertainty in ESI modelling exists at each stage of the process; from options generation to the selection of a preferred solution. Different methods have been used to deal with different types of uncertainty, in different phases of the process. At issue when considering uncertainty are the concepts of "robustness" and "flexibility" of the solutions generated [27–30]. In the context of ESI modelling, robustness can be defined as the degree to which a solution is affected (in terms of cost or any other attribute) by unknown future parameters or changing assumptions [28,31]. Flexibility can then be defined as the degree to which a solution can be adapted at a future point in time (without substantial loss/change of performance in relation to the objectives), and in light of the resolution of, or changing opinions about, unknown future parameters [28,31,32]. It can then be said that a robust solution will perform well under a range of unknown futures, while a flexible solution could easily be adapted to changing future conditions at minimal loss of performance in relation to the objectives. These two concepts are key to the methodology developed here, and will be explored in the case study of Section 4. Before doing so, however, there is merit in describing two of the most relevant methods[4] used to account for uncertainty and multiple objectives in the options generation phase: the "trade-off/risk approach"; and stochastic programming. These are discussed in turn below.

The trade-off/risk approach (developed by Merrill and Schweppe [33]) emphasises the trade-offs between objectives and the identification of robust solutions rather than finding a single optimal solution for a given system. Principles of this method were used in an electricity sector trade-off analysis whereby multiple objectives were addressed under conditions of demand and fuel price uncertainty through the generation of future scenarios [34]. Through the process of stakeholder interaction, a range of possible future technology configurations was generated. Overlaying the range of modelling uncertainties onto this set of options allows a large number of permutations to be simulated. EGEAS,[5] a single objective, least-cost power expansion analysis tool, was used for this purpose. This vast solution set was then reduced by screening out consistently inferior solutions based on predefined objectives. The reduced solution set was evaluated against all proposed futures to determine the performance of each solution for the given objectives under uncertainty. In this way solutions that were both robust to the uncertainties involved and that performed well under all of the objectives were isolated.

While this analysis is valuable and can provide policy makers with insight into the problem and the trade-offs involved, it has the disadvantage of generating a set of both dominated and non-dominated solutions from which efficient solutions need to be chosen, as well as the disadvantage that individual solutions do not have inherent flexibility in the face of uncertainty. Optimality can be traded-off against robustness when using this method, due to the fact that many efficient solutions may not form part of the solution set. This is because the solution space is generated by predefined scenarios based on technology configurations rather than from the objectives themselves. While it is agreed that solutions that are robust to uncertainty are often preferable to decision makers than solutions that are efficient alone [35], it is argued that solutions that are both efficient and robust (especially if there are numerous objectives) may be missed by generating the solution space based on predefined scenarios with regard to technology configurations rather than from the objectives themselves. It is, however, acknowledged that a robustness analysis is essential to energy modelling and should be integrated into any comprehensive ESI modelling methodology.

Stochastic programming techniques have been used to model uncertainty in the ESI since the 1980s [32,36–38]. This was generally done through use of multiple cost-based objective functions (each representing a different future state of the world) which were weighted according to the probabilities of each state of the world. Minimising the overall objective function then resulted in minimising the total expected system cost for all futures and building flexibility towards cost into the power station mix in light of the uncertainties considered.

Stochastic programming models with recourse [39] are used for near term modelling in light of long-term uncertainties through the development of short-term strategies with inherent flexibility towards long-term uncertainties, as well as long-term contingency plans once more information becomes available about the uncertain parameters. The recourse problem is formulated with different future states of the world coming into being after designated points in the time horizon (see Fig. 1 for an example of the two-stage problem). This is different to stochastic programming without recourse, which outputs a single strategy for the entire time horizon which is optimal, on average, for all scenarios. The recourse solution is then optimised such that each stage of the model is best positioned to meet the multiple future conditions, thus including an aspect of flexibility in the solution. Two-stage stochastic programming is best suited for modelling future uncertainties that have a definite date of resolution (such as

[4]Other methods for considering the uncertainty in decision maker preferences or objectives such as interval and possibilistic programming are not discussed here but are considered in the plan selection phase. The approach here is to generate a representation of the non-dominated solution set from which a preferred solution can then later be selected.

[5]EGEAS (Electric Generation Expansion Analysis System) developed by the Electric Power Research Institute (EPRI), http://www.epri.com.

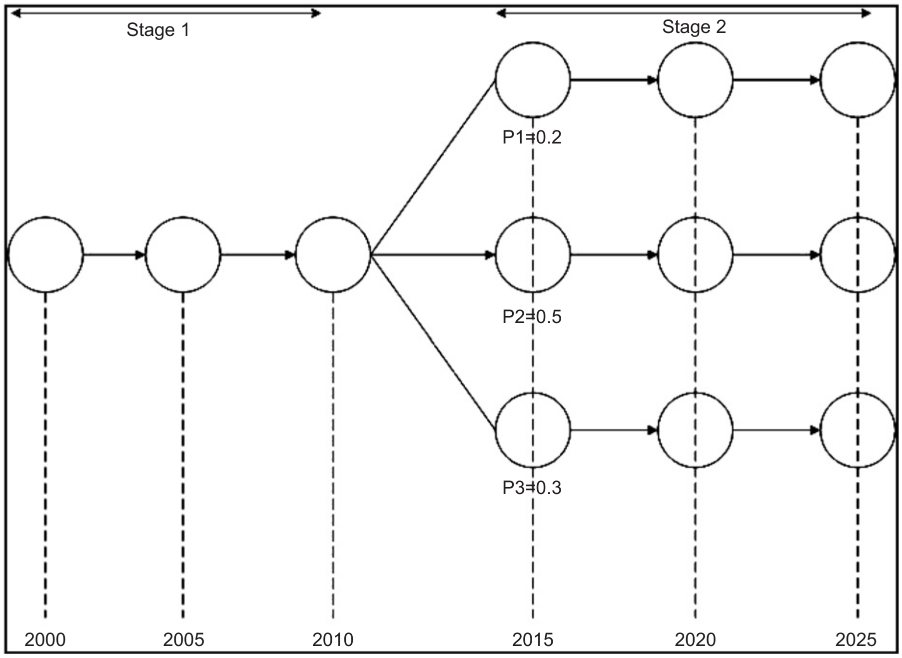

Fig. 1. Example of an event tree with three states of the world and resolution time at 2015.

legislation associated with emission limits) but it can also be used to model demand growth and fuel price uncertainties e.g. [37,40]. Stochastic modelling with recourse has also been used to generate flexible least-cost solution strategies for global climate change [27].

Note that, with regard to the simultaneous consideration of multiple objectives, all three classes of methods for locating efficient solutions to MOLP models described in Section 2.1 are applicable to stochastic models [41].

2.3. Rationale for methodology

Of the methods for considering multiple objectives described above, a weighted sum or composite distance approach cannot be readily used within existing single objective energy planning approaches without significant reformulation of the tools. However, both a constraint-based method and a cost penalty-based method could easily be applied within these frameworks to explore multiple objectives.

Stochastic programming with recourse is a powerful technique for addressing future uncertainties (such as demand growth) due to the incorporation of flexibility within a dynamic optimisation framework. It has the advantage of generating only non-dominated solutions as the solution space is generated from the objectives themselves rather than from predefined technology mixes. While stochastic programming methods have included multiple objective functions to represent different future states of the world e.g. [32,36–38], they have not been extended to include multiple (environmental or social) objectives into the power expansion problem formulation.

When considering both multiple objectives and uncertainty, using a cost penalty-based method, as opposed to a constraint-based method, has the advantage of extending the recourse modelling to include flexibility to uncertainty for all objectives, whereas a constraint-based method would only include flexibility to cost. This is due to the inclusion of the cost penalties into the model's objective function and therefore into the hedging action taken by the recourse approach. It also has the advantage of providing policy makers with an indication of the market signals necessary to influence the market towards a preferred state in the form of emission taxes.

This method can, however, be manually intensive as it does not guarantee a well-spread representation of the non-dominated solution set. The burden of ensuring such a representation now lies with the modeller. Unlike with constraint-based methods, the performance value of each attribute for each solution is obtained as ;an output of the model rather than specified as an input (with cost penalties being the changing input parameter causing the objective function to find new solutions). The additional effort required by the modeller to ensure a well-spread representation of the non-dominated solution space is considered a necessary trade-off for the benefits of using the cost penalty-based approach stated above.

With this in mind, the proposed approach to ESI modelling adopted here relies on an extension of the two-stage recourse problem for multiple objectives using a cost penalty-based method. The full methodology is described in Section 3.

3. Methodology

3.1. Generating a base case scenario

The first step in the proposed modelling process is to develop a base case or "business as usual" scenario, using a least-cost optimisation approach. This can be done using energy planning models such as MARKAL,[6] EGEAS, MESSAGE[7] which typically include a complete supply side representation (including all costs and emission coefficients) of all existing power stations in the system, as well as a range of technology options for future stations. The models operate within a series of constraints that must be satisfied in order for a solution to be considered feasible. Such constraints typically include mass and energy balances, meeting demand projections, satisfying peak and base-load requirements within a given reserve margin, obeying emission constraints as well as any technology specific constraints. The base case scenario is then simply the least-cost optimised solution for the represented power system.

3.2. Extension of solution set to include multiple objectives

The next step in the proposed methodology is to expand the solution set from the base case scenario by the inclusion of other objectives, which will likely result in technology options not present in the base case scenario.

Our approach here is to expand the solution set to satisfy multiple objectives using a dynamic partial equilibrium optimisation framework. Here, cost penalties are introduced in the model to capture the performance of technology options in those attributes which relate to the "non-cost" objectives. The least-cost objective function is retained in the optimisation, but due to the cost penalties, the solution space is now searched for non-dominated solutions that force the model to better satisfy the non-cost objectives (consistent with the first approach discussed in Section 2.1). This is explained in more detail below.

The MARKAL model objective function, described in [42], can be summarised mathematically as follows:

$$NPV = \sum_{t=1}^{t=NPER} (1+d)^{NYRS^*(1-t)} \bullet ANNCOST(r,t) \bullet (1+(1+d)^{-1}+(1+d)^{-2} + \cdots + (1+d)^{1-NYRS}), \quad (1)$$

where NPV is the net present value of the total cost to be minimised (the objective function), $ANNCOST(r,t)$ is the annual cost for period t, in region r, d is the general discount rate, $NPER$ is the number of periods in the planning horizon, $NYRS$ is the number of years in each period t.

Various decision variables, which represent the choices made by the model to minimise total cost, are considered within this MARKAL model, as described in [42]. Some of these are elaborated on here:

$INV(r,t,k)$: new capacity addition for technology k, in period t, in region r.
$CAP(r,t,k)$: installed capacity of technology k, in period t, in region r.
$ACT(r,t,k,s)$: activity level of technology k, in period t, in region r, during time-slice s.
$ENV(r,t,p)$: emission of pollutant p in period t in region r.

The total annual cost $ANNCOST(r,t)$ is the sum over all technologies k, and all input fuels f, of the various costs incurred, namely: annualised investments, annual operating costs (including fixed and variable technology costs, fuel delivery costs, costs of extracting and importing energy carriers), minus revenue from exported energy carriers and taxes on emissions. Mathematically, $ANNCOST(r,t)$ is expressed as follows:

$$\begin{aligned} ANNCOST(r,t) &= \sum_{\mathrm{k}} \{Annualised\_Invcost(r,t,k) * INV(r,t,k) \\ &+ Fixom(r,t,k) * CAP(r,t,k) \\ &+ Varom(r,t,k) * \sum_{s,s} ACT(r,t,k,s) \\ &+ \sum_{\mathrm{c}} (Delivcost(r,t,k,c) * Input(r,t,k,c) \\ &* \sum_{s} ACT(r,t,k,s))\} \\ &+ \sum_{c,s} \{Miningcost(r,t,c,l) * Mining(r,t,c,t) \\ &+ Importprice(r,t,c,l) * Import(r,t,c,l) \\ &- Exportprice(r,t,c,l) * Export(r,t,c,l)\} \\ &+ \sum_{c} \{Tax(r,t,p) * ENV(r,t,p)\}, \end{aligned} \quad (2)$$

where $Annualised\_Invcost(r,t,k)$ is the annual equivalent of the lump sum unit investment cost, obtained by replacing this lump sum by a set of equal annual payments over the life of the equipment, in such a way that the present value of the stream is exactly equal to the lump sum unit investment cost, for technology k, in region r and period t; $Fixom(r,k,t)$, $Varom(r,t,k)$, are unit costs of fixed and operational maintenance of technology k, in region r and period t; $Delivcost(r,t,k,c)$ is the delivery cost per unit of commodity c to technology k in region r and period t;

[6]MARKAL (MARKet AnaLysis) developed by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency, http://www.etsap.org.

[7]MESSAGE (Model for Energy Supply Systems Analysis and their General Environmental impact) developed by the International Institute for Applied Systems Analysis (IIASA), http://www.iiasa.ac.at/Research/ECS/docs/models.html#MESSAGE.

Input(*r*,*t*,*k*,*c*) is the amount of commodity *c* required to operate one unit of technology *k*, in region *r* and period *t*; *Miningcost*(*r*,*t*,*c*,*l*) is the cost of mining commodity *c* at price level *l* in region *r* and period *t*; *Importprice*(*r*,*t*,*c*,*l*) is the import price of commodity *c* in region *r* and period *t*; *Exportprice*(*r*,*t*,*c*,*l*) is the export price of commodity *c* in region *r* and period *t*; *Tax*(*r*,*t*,*p*) is the tax on emission *p* in region *r* and period *t*.

The objective function is then minimised subject to the following constraints.

Satisfaction of demands: For each time period *t*, region *r*, demand *d*, the total activity of end-use technologies servicing that demand must be at least equal to the specified demand. Hence

$$\sum_{\text{Over all } k} CAP(r,t,k) \geqslant D(r,t,d). \tag{3}$$

Capacity transfer: For each technology *k*, region *r*, period *t*, the available capacity in period *t* is equal to the sum of investments made by the model at past and current periods, and whose physical life has not ended yet, plus capacity in place prior to the modelling horizon and still in place:

$$CAP(r,t,k) = \sum_{t'}^{t} INV(r,t',k) + RESID(r,t,k), \tag{4}$$

where *RESID*(*r*,*t*,*k*) is the capacity of technology *k* due to investments that were made prior to the initial model period and still exist in region *r* at time *t*.

Use of capacity: For each technology *k*, period *t*, region *r*, and time-slice *s*, the activity of the technology may not exceed its available capacity, as specified by a user defined availability factor

$$ACT(r,t,k,s) \leqslant AF(r,t,k,s) * CAPUNIT * CAP(r,t,k), \tag{5}$$

where *CAPUNIT* is the unit of activity/unit of capacity (e.g. PJ/MW).

Energy balance: For each commodity *c*, time period *t*, region *r*, and time-slice *s* in the case of electricity, this constraint requires that the disposition of each commodity may not exceed its supply. The disposition includes consumption in the region plus exports; the supply includes production in the region plus imports,

$$\begin{aligned}&\sum_{\text{Over all } k} Output(r,t,k,c) \bullet ACT(r,t,k,s)\\ &\quad + \sum_{\text{Over all } l} Mining(r,t,c,l)\\ &\quad + \sum_{\text{Over all } l} FR(s) \bullet IMP(r,t,c,l)\\ &\quad\geqslant \sum_{\text{Over all } l} Fr(s) \bullet EXP(r,t,c,l)\\ &\qquad + \sum_{\text{Over all } k} Input(r,t,k,c) \bullet ACT(r,t,k,c,s),\end{aligned} \tag{6}$$

where *Input*(*r*,*t*,*k*,*c*) is the amount of commodity *c* required to operate one unit of technology *k*, in region *r* and period *t; Output*(*r*,*t*,*k*,*c*) is the amount of commodity *c* produced per unit of technology *k*, and *FR*(*s*) is the fraction of the year covered by time-slice *s* (equal to 1 for non-seasonal commodities).

Electricity and heat peak reserve constraint: For each time period *t* and for region *r*, there must be enough installed capacity to exceed the required capacity in the season with largest electricity (heat) commodity *c* demanded by a safety factor *E* called the *peak reserve factor*.

$$\begin{aligned}&\sum_{\text{Over all } k} CAPUNIT \bullet Peak(r,t,k,c) \bullet FR(s)\\ &\quad \bullet CAP(r,t,k) + FR(s) \bullet IMPORT(r,t,c)\\ &\qquad \geqslant [1 + ERESERVE(r,t,c)] \sum_{\text{Over all } k} Input(r,t,k,c)\\ &\quad \bullet FR(s) \bullet ACT(r,t,k,s) + FR(s) \bullet EXPORT(r,t,c),\end{aligned} \tag{7}$$

where *ERESERVE*(*r*,*t*,*c*) is the region-specific reserve coefficient, which allows for unexpected down time of equipment, for demand at peak, and for uncertain hydro-electric, solar, or wind availability.

Peak(*r*,*t*,*k*,*c*) (never larger than 1) specifies the fraction of technology *k*'s capacity in a region *r* for a period *t* and commodity *c* (electricity or heat only) that is allowed to contribute to the peak load.

As mentioned above, additional objectives are considered through the use of cost penalties, hereafter called Pareto generation parameters (PGPs), which operate on the cost minimisation objective function. These are incorporated in the model as emission taxes and act directly on the investment (*INV*(*r*,*t*,*k*)) and activity (*ACT*(*r*,*t*,*k*,*s*)) decision variables through the pollutant emission parameter (*ENV*(*r*,*t*,*p*)). Individual emission tax parameters are defined using the *Tax*(*t*,*p*) parameters in the model (described below).

As total system cost is minimised through the objective function, the model attempts to minimise emissions because of the cost penalty associated with each emission defined using the *Tax*(*t*,*p*) parameters. The degree to which the model will improve the attribute performance of each of the non-cost objectives depends on the magnitudes of the PGPs, as the costs associated with the emissions (through the *Tax*(*t*,*p*) parameter) are traded-off against the other system costs in the optimisation. Therefore by varying the emission tax values for each PGP, the model will provide a range of solutions that satisfies each of the non-cost objectives to varying degrees. The challenge is to ensure that a representative range of emission taxes is considered for each additional objective, so that the expanded solution set includes adequate diversity in technology options within each scenario to address stakeholder interests. This approach is outlined below, and demonstrated in the case study of Section 4.2.

These PGPs resemble externality costs[8] in that monetary values are assigned to by-products of the electric supply process (in the form of emission taxes). The difficulty in calculating externality costs is widely acknowledged, with different methods yielding different values for the same problem (see for example [43,44]). The value of using externality costs for guidance in policy decisions, despite the uncertainties involved, is discussed in [45]. However, in this method, the PGPs are merely used as parameters to generate a representation of the multi-objective solution space. No claim is made that the PGPs represent the actual monetary cost for any damages suffered by humanity or the environment[9] due to the electricity generation process. These values are determined iteratively based on the performance ranges of the non-cost attributes that stakeholders wish to investigate (discussed below).

An algorithm to generate a representation of the non-dominated solution space is outlined below:

- Decide on a set of non-cost criteria to include into the optimisation. There is a real need to consider the environmental and social aspects of sustainability in ESI modelling. Taking this as our starting premise, we limit our consideration to selected environmental issues by way of demonstration, and here focus on a range of impacts which span global, regional and local spatial and temporal scales, and which we believe to be of genuine concern to stakeholders. The non-cost criteria chosen to illustrate the methodology in this paper were: climate change potential, acidification potential, and water consumption.
- Identify attributes within the model that relate to each of these criteria, e.g. all contributions to potential climate change are measured in equivalent units of CO_2 emissions; acidification potential is defined in terms of SO_2 equivalents; and specific water consumption is the total water volume consumed. These are consistent with attributes used in environmental impact assessment approaches such as Life Cycle Assessment (see ISO 14040 series of standards [46]). However, in this model, the spatial footprint of these attributes is not considered on a full life-cycle basis, but limited to a consistent process boundary for all technologies which make up a given energy plan.
- Define a range of PGPs for each of the attributes such that an acceptable range of performance is achieved for each attribute in the model. These ranges are defined by stakeholder interests; for example, by setting performance targets in the environmental objectives as defined fractions of their value in the base case (least-cost solution). This can be done for each additional criterion individually by testing the effect that different PGP values have on the base case. This effect will be determined by the technologies (existing and new) in the model, and their emission coefficients and specific water consumption values. The range of values for each PGP is defined, such that the solution corresponding to the highest PGP value achieves the necessary performance levels defined by DM in the corresponding non-cost attribute. In this way, the effect that each PGP individually has on the final solution (in terms of attribute scores and the build plan) is demonstrated unambiguously. The combined effect of using different PGPs simultaneously may generate solutions whose performance exceeds the required performance level for each individual attribute. Should this be so, it would be necessary to screen solutions (see Section 3.3), both to reduce the number of solutions, and to focus on a section of the solution space of interest to the DM (which is identified by stakeholder engagement). The specific PGP values which give rise to the extremities of the performance ranges of each attribute can be identified straightforwardly, and serve as a check on stakeholder acceptability. These extremes may be modified progressively as stakeholder understanding of the problem develops.
- Once a satisfactory range has been determined for each PGP individually (based on the stakeholder-defined ranges in attributes), each range must then be sampled so that the solution space can be explored. Enough values should be chosen so as to allow for individual attribute performance as well as interactions to be seen, bearing in mind that the number of model runs will increase exponentially with the number of samples from each PGP range. This choice is therefore case study and user dependent.
- The model is then rerun for all permutations of the samples of the PGPs determined above. This maps out a space of non-dominated solutions spanning ranges in performance for each of the attributes represented by the PGPs. In this way, the model can be seen to accommodate multiple objectives.

3.3. Screening options for further analysis

At this stage, the solution space contains only non-dominated solutions. However, the number of options in this set could be unmanageable due to the exponential effect of the number of criteria, and the number of PGPs values chosen to explore those criteria. Screening for financial viability and other stakeholder-defined constraints such as technology diversity, technical risk, reserve margin or minimum performance parameters in any of the attributes can be done at this stage to reduce the solution set before further analysis is conducted. The intention here is merely to reduce the solution set to a manageable number of options for subsequent detailed analysis of uncertainty.

[8]Externality costs can be defined as the "damages" or "unpaid value" of environmental damage caused by, in this case, electric power services [12] but paid for by society as a whole.

[9]However, it is possible to make inferences from the PGP values that produce the set of power station investments that are ultimately selected based on policy maker preferences.

3.4. Modelling future uncertainties

Up to this stage of our analysis, the effects of uncertainties have not been considered explicitly. However, even after screening, the number of solutions that remain would still be far in excess of what could realistically be considered in detail; hence conducting the preceding analysis steps without explicit consideration of uncertainty is not considered to be of adverse consequence. However, the effect of uncertainty needs to be taken into account for the remaining (i.e. screened) sub-set of options. For example, the solutions need to be robust to different future states of the world (such as different fuel prices) and need to have built-in flexibility to meet unknown futures (such as differences in demand growth). This can be addressed using hedging, or ''least regret'' strategies.

3.4.1. Stochastic modelling with recourse

It is proposed that future uncertainties such as demand growth can be modelled using stochastic programming with recourse, as has been used previously to increase the flexibility of power expansion plans [27,37].

Demand growth was chosen as the future uncertainty parameter to demonstrate this methodology. It is different to other technical empirical parameters in expansion planning in that the penalty that would be paid for not meeting demand requirements would be system failure, rather than merely poor performance in an objective. This is part of the reason why reserve margins are included into the planning process. However, in some cases these may not provide sufficient protection against demand growth uncertainty. It was therefore decided to integrate demand growth uncertainty into the generation phase using stochastic programming with recourse to ensure flexibility towards this uncertainty.

3.4.2. Accounting for technology lead times

Fundamental to this recourse problem is the concept of technology lead times (especially when addressing demand growth uncertainty). Because power stations have long lead times, decisions to build or get a station to the ''ready to build'' stage need to be made well in advance. In deterministic models, planners incorporate lead times by setting constraints on the investment parameters of technologies, until their lead times have passed. In stochastic programming with recourse the concept of a lead time for each new technology has to be accounted for at the beginning of the time horizon and then again at the decision node, if hedging for the uncertain future is intended. It would be inconsistent for the model to build a technology immediately after the decision node in one future and not another as this would violate the concept of technology lead times. In the work presented here, this problem has been addressed by splitting power station investments for each major new technology into two irreversible phases, namely the owners' development cost (ODC) and the cost of the equipment procurement and construction (EPC), each with their corresponding lead times.[10]

Splitting investments into phases introduces aspects of real options theory [48], in which there is a value assigned to delaying an investment. Initial investments (ODC investments) into a technology may be made to ''buy'' time; to ''wait and see'' what happens with future uncertainties, and whether, under such conditions, the technology may be an economically viable option. This initial investment can then either be taken further to the full development and execution of the technology (EPC phase) when uncertainty unfolds, or the initial investment it can be written off as a loss if the uncertainty unfolds in a way which would make it uneconomical to build this technology.

In this way, the model is allowed to build capacity in the second phase of a technology (EPC phase) only when that generating capacity has previously been brought to the ''investment ready'' stage in the first (ODC) phase. The implication of this is that ODC investment is limited to before the decision node for the stochastic model. This forces decisions (and primary investments) to be made before the resolution of uncertainty, hence hedging for future uncertainty. This methodology can create discrepancies in lead times for technologies built towards the end of the time horizon, as it forces all initial decisions (and investments) to be made before the decision node, when in reality some of these decisions could be made at a later stage. This could be remedied by allowing technologies at the end of the time horizon to be built as a single entity (instead of splitting them up) as long as their lead times requirements are not violated.

3.4.3. Expected cost of ignoring uncertainty (ECIU)

In order to evaluate the benefit of using stochastic programming with recourse (as opposed to a more routine deterministic approach) a quantity called the ECIU, see [49], can be constructed. This is achieved by creating an equivalent stochastic scenario for each set of PGPs (called the naïve solution), where the probability of the median future occurring is almost 100% (unlike the hedged solutions where the probabilities of the non-median futures have significant values). This forces the model to ignore the fact that multiple futures can occur when hedging for the second stage of the solution, and creates a new solution that contains multiple futures after the resolution date but where no hedging has been done for those futures. The hedged solution can then be compared to the naïve solution to determine the value of explicitly considering uncertainty using stochastic programming. In a single objective optimisation exercise, the total discounted system cost of the naïve solution could be compared to that of the hedged solution. In this case, due to the inclusion of PGPs into the

[10]The ODC component typically constitutes a minor component of the total investment cost for a power station when compared to the EPC cost [47].

model runs as a means of extending the analysis to multiple objectives, the performance in both cost and the other predefined non-cost attributes can be compared. This, in our view, is a powerful extension of the approach.

A major difference between the stochastic modelling done in previous work [27,32,36–38] and the work presented here is that the previous work generally focussed on using several probability weighted cost-based objective functions to model different states of the world, while this work extends that formulation to include multiple environmental objectives as well.

The stochastic variant of MARKAL (see appendix for equations) redefines the objective function shown previously (Eqs. (1) and (2)) so that the overall objective function becomes the weighted sum of the expected costs for each state of the world, weighted by their probability of occurrence. The hedging that is done in the recourse programming is then automatically translated from purely financial to include whatever attributes the PGPs represent due to the cost penalties that the PGPs impose on the objective functions for each state of the world. This implies that the model will attempt to minimise both cost and non-cost criteria in light of the uncertain futures involved. However, due to the cost penalties that the PGPs impose, the model may find it optimal to reduce non-cost attributes over cost, for a particular set of PGPs. This could result in some hedged solutions being more expensive than naïve solutions for the same scenario (which cannot happen in a scenario without PGPs). However, the hedged solution would then have better performance in other attributes than the naïve solution.

This type of analysis enhances the multi-objective nature of the proposed methodology by including multiple criteria into the hedging process for future uncertainty. Aspects of uncertainty can be addressed in terms of multiple criteria rather than a single criterion and therefore the entire options generation process can be explored in a more holistic manner in relation to multiple objectives.

3.4.4. Uncertainties not directly addressed

Although fuel price and other data uncertainty (capital costs, O&M costs, emission coefficients, etc.) have not been directly addressed within this paper they are addressed in a follow-on paper dedicated specifically to the ranking and selection of preferred alternatives under data, fuel price and valuation uncertainties [4]. Table 7 in the appendix outlines some of the key parameters in the plan generation phase of this problem, where the data came from and how uncertainty in each of the parameters is typically handled.

The model could be adjusted to deal with uncertainty relating to technology change through endogenous technology learning (ETL), already a feature of some existing energy models (see for example MESSAGE [50], MARKAL [51], POLES [52,53], and ERIS [54]).

While market liberalisation has not been directly addressed in this work, partial equilibrium frameworks provide results that are valid for both regulated, centrally planned power markets, as well as for efficient fully deregulated markets. The short-term effects of market liberalisation may be better modelled using system dynamics, agent-based modelling or game theory, where the interaction between firms in specific market environments are accounted for (see for example [2,55]). However, the current methodology and results would still be valid for centralised planning of a competitive market (i.e. from the perspective of a regulator or policy maker).

4. Case study: The South African power sector

The case study used to illustrate the proposed methodology is the South African electrical power sector. South Africa currently has a regulated and centralised, mainly coal-based generation portfolio (93% of the 39 716 MW_e installed capacity in 2002 [47]) due to the abundance of "cheap" coal available. The country also has small amounts of nuclear (5%) and pumped storage/hydro power (2%). South Africa's base load coal power stations burn pulverised coal. Electrostatic precipitators are used for particulate removal, although bag filters are installed on a few stations. To date, there is no desulphurisation technology installed on any plant (although, in some cases, some removal of pyritic sulphur occurs during coal cleaning). Emission of nitrogen oxides is limited only through use of low-NOx burners. Due to the local water shortage problem, advanced water saving technologies, which include dry cooling and dry ash disposal have been deployed on some stations, which results in South Africa's newer coal stations being amongst the most water efficient in the world [56]. South Africa is now at a critical stage in its development, where it is necessary to decide on which power stations to build in the future to meet increasing demand. The problem is compounded by the age of many existing coal-fired stations as well as significant challenges relating to water availability and regional air quality.

4.1. The base case

The "base case" was set up to represent the South African ESI, including the existing generating system and a range of viable future technologies to meet the growing (median) demand. We take as our starting point the power station data and the "moderate" demand data (see appendix) used for the National Integrated Resource Plan (NIRP) of the National Electricity Regulator [47]. This data was reviewed by local stakeholders and experts during the NIRP process. We use this data as a basis for our study, and consider aspects of uncertainty around these. It should be noted, however, that in future studies the basic data could well be expanded. For example, though nuclear power station costs include estimates for decommissioning, a full life-cycle representation of the nuclear cycle would be useful (together with an analysis and formal treatment of the uncertainties therein). Electricity demand was assumed to be inelastic, due

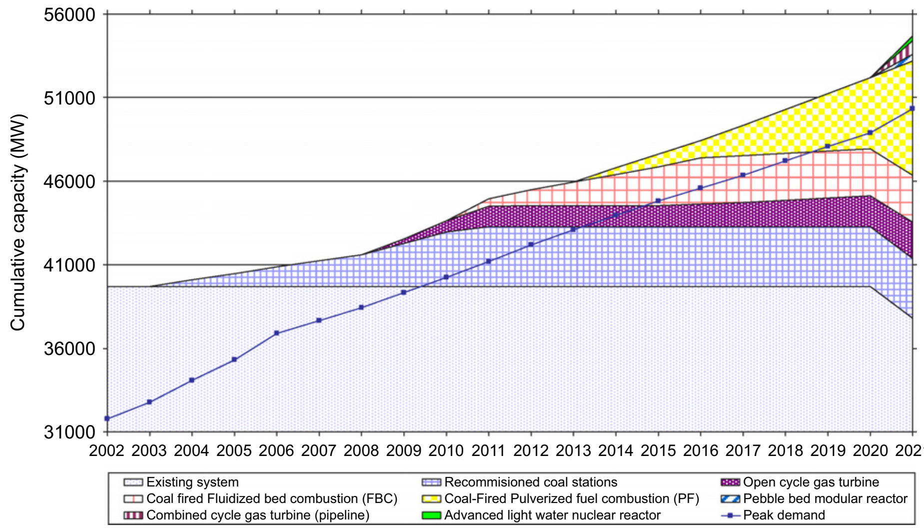

Fig. 2. Technology capacity summary for BASE case.

in part to the low cost of electricity production.[11] Detailed technology and economic data as well as the assumptions[12] used for the case study were based on the NIRP and can be downloaded from http://www.ner.org.za. The base case also includes investments that are already committed to, such as the recommissioning of out-of-service coal stations and a pumped storage scheme, as well as demand side management (DSM) projects.

Costs (investment and O&M) as well as emission coefficients and specific water consumption coefficients were included for all technologies considered. Using the Inter-Governmental Panel on Climate Change (IPCC) characterisation factors [59] for direct global warming potential, and the (Danish) Environmental Design of Industrial Products (EDIP) effect factors [60] for acidification potential, the emission coefficients were converted to CO_2 and SO_2 equivalents to represent the criteria of global climate change and regional acidification potential. The issue of water consumption was also chosen as a criterion due to its local relevance in South Africa. Note that costs and emissions were not accounted for on a life-cycle basis. Given that the goal of this paper is to present a new methodology, this is not considered to be a limitation. However, where the goal would be to develop defensible plans for the South African ESI, the consideration of costs and emissions on a full life-cycle basis is considered essential.

The base case was explored as a least-cost optimisation exercise in MARKAL, over a time horizon of 20 years (matching the NIRP), and starting in 2002 (so as to include some historical data into the model). A discount rate of 8% was used in the case study (based on the NIRP) representing a private investor market in South Africa. However, in the light of sustainable development; a lower discount rate could be used (see [61,62] for discussions on the use of social discount rates for sustainable development), thereby allowing investments to occur earlier than depicted in Fig. 2.

Fig. 2 illustrates an investment summary for the base case scenario[13] over the time horizon.

It can be seen from Fig. 2 that most of the investment in new capacity in the base case scenario is in coal-fired power stations (PF and FBC). There is also significant investment in open cycle gas turbines (as peak load stations) and a small investment into nuclear technologies and combined cycle gas turbines right at the end of the time horizon to replace the existing capacity that is assumed to be decommissioned in 2021.

4.2. Extending the solution set to consider multiple objectives

Following the methodology outlined in Section 3, explicit consideration was given to global impacts such as climate change and regional impacts such as local air quality (due to South Africa's high coal plant density region—Mpumalanga) and water consumption (due to national water shortages). This was done by introducing cost penalties on CO_2-eq emissions, SO_2-eq emissions and water consumption into the least-cost model.

A range of five levels for each PGP was chosen to generate a representation of the non-dominated solution

[11] In the case of South Africa, due in part to the low cost of electricity, price elasticities are very low [57,58]. This analysis could be extended to include detailed demand response if the electricity price were to increase significantly.

[12] A conversion rate of R9/US$ was used as per the NIRP.

[13] This solution set was generated using linear programming assuming all variables to be continuous rather than using mixed integer linear programming. It would be valuable in further work to extend this analysis such that investment would occur in technologically consistent blocks rather than continuously.

Table 1
PGP values and attribute performance results the base case and ALT 11

PGPs (kZAR/kton)	Base case	Alternative 11	Base case with tax
CO_{2EQ} emissions	0	0.00	0.00
SO_{2EQ} emissions	0	24 424	24 424
Water consumption	0	16	16
Cost (kZAR)	2.621E+08	2.732E+08	2.621E+08
CO_{2EQ} emissions (kton)	2.658E+06	2.513E+06	2.658E+06
SO_{2EQ} emissions (kton)	1.564E+04	1.478E+04	1.564E+04
Water consumption (kton)	4.309E+06	4.073E+06	4.309E+06
Total cost including tax (ZAR)	2.621E+08	6.978E+08	7.114E+08

space. This allows representative sampling of the solution space. This yielded 105 different solutions (including the BASE case) with a diverse range of technology configurations which resulted in reductions of up to 30% in CO_2 equivalent emissions, up to 33% in SO_2 equivalent emissions, and up to 48% in water consumption. These solutions spanned a cost range up to an increase of almost 100% over the base case. Given this last figure, the range of options generated by this method was deemed to be sufficient for subsequent analysis, and demonstration of the methodology.

To demonstrate how the non-cost attributes are considered in the model, the performance of one particular alternative (Alternative 11), which is considered in some detail, is examined. Table 1 shows the performance of Alternative 11 against the "base case".

Alternative 11 was generated when a specific value of emission tax was introduced for SO_{2EQ} emissions and water consumption. Here, a tax of ZAR 24423.75/ton was defined using the $Tax(t,p)$ parameter, to introduce a cost penalty on all SO_{2EQ} and a tax of ZAR 15.62/ton was defined using the $Tax(t,p)$ parameter, to introduce a cost penalty on all water consumption in the model. If the investment and operational decision variables ($INV(r,t,k)$) and $ACT(r,t,k,s)$, respectively) were to remain unchanged from their values in the base case, the overall system cost including tax would have become 7.114E+08 kZAR. However, as the objective function attempted to minimise overall system cost (including the cost penalties to capture environmental performance), investment into, and the operation of high SO_{2EQ} emission producing and water consuming technologies was reduced. This resulted in investment Alternative 11 (described in more detail in Section 4.3), having a higher total discounted system cost (excluding taxes), but lower CO_{2EQ} and SO_{2EQ} emissions and water consumption values than those of the base case. This reduction in emissions resulted in Alternative 11 having a lower total system cost including taxes (6.978E+08) than the base case scenario with taxes included. This demonstrates how using PGPs forces the model's least-cost objective function to minimise emissions and therefore better satisfy non-cost objectives.

4.3. Screening of options for further analysis

The 105 solutions generated in this manner were then screened on financial performance assuming a hypothetical threshold of 20% above base case total discounted system cost,[14] which amounted to an increase in cost of 50 billion ZAR (in 2004 terms) over the base case. The hypothetical threshold was chosen to demonstrate the proposed methodology for a reduced solution set containing a diverse range of attribute performances. The solutions could also have been screened at this stage on other user defined constraints or attribute performances.

The screening on total discounted system cost resulted in retention of the following set of alternatives, where their attribute performance values are shown relative to the base case (where minus signs denote a decrease from the base case).

The new solution set shown in Table 2 contains the base case and the remaining non-dominated alternatives after screening. It can be seen from Table 2 that, as the cost of each alternative increases, performance in the non-cost attributes improve. It must be noted that not all of the non-cost attribute performances correlate with increasing cost. Due to a degree of compensation between performances in the various non-cost criteria, it is not necessary that improvements in all the non-cost attributes occur simultaneously with increasing cost. Reductions in emissions and water consumption are mainly due to increased investment in "cleaner" technologies such as nuclear and gas, as illustrated for Alternative 11 in Fig. 3, whereas the base case mainly invested in coal-based generation.

As can be seen from Fig. 3, Alternative 11 invests in significant amounts of nuclear power.[15] There are also

[14]Note: total discounted system cost is the true cost and does not include the attribute cost penalties.

[15]The cost of decommissioning nuclear power stations was included into the investment cost of the power stations although the environmental effects of spent nuclear fuel were not quantified, nor were they listed as specific decision criteria. Where the intent is to generate defensible plans for the South African ESI, the consideration of a more comprehensive set of impacts, including those associated with waste management for the different kinds of technologies, is considered essential.

small investments in open cycle gas turbines and wind power at the end of the time horizon. This results in the decrease of over 5% in CO_2-eq and SO2-eq emissions as well as a decrease in water consumption of over 5%. These environmental improvements compared to the base case can be gained at an increase in cost of less than 4.5%.

The solution set thus contains solutions with varying technology mixes which result in a diverse range of attribute performance values. Each solution represents a different trade-off between the various criteria that would have to be evaluated by the policy makers. The selection of a preferred solution will not be elaborated upon in this paper, but forms the second phase of the proposed methodology which is described in the follow-on paper [4].

Table 2
Attribute performance ranges for screened solution set

Cost (%)	CO_2-eq (%)	SO_2-eq (%)	Water	Alternative consumption (%)
BASE	0.00	0.00	0.00	0.00
ALT 1	0.19	0.72	0.61	−9.13
ALT 2	0.35	−0.25	0.10	−8.71
ALT 3	0.35	−3.73	−1.96	9.75
ALT 4	0.36	0.76	−0.14	−9.18
ALT 5	1.05	0.40	1.13	−10.71
ALT 6	1.07	0.27	−0.29	−10.24
ALT 7	1.41	−0.17	0.80	−10.99
ALT 8	1.52	−4.21	−2.80	−4.60
ALT 9	2.29	−1.49	−1.80	−10.49
ALT 10	2.99	−6.39	−3.98	9.62
ALT 11	4.21	−5.47	−5.52	−5.48
ALT 12	5.37	0.04	1.22	−14.82
ALT 13	5.83	−1.41	0.33	−14.83
ALT 14	6.17	−7.38	−3.93	−6.66
ALT 15	6.43	−7.01	−6.76	−5.88
ALT 16	6.98	−8.27	−5.74	8.83
ALT 17	7.60	0.26	−0.61	−16.32
ALT 18	8.87	0.04	0.48	−17.54
ALT 19	13.03	−9.65	−9.56	−9.62
ALT 20	13.77	−10.29	−9.11	−10.10
ALT 21	14.84	−10.66	−9.48	−10.66
ALT 22	15.07	−10.45	−10.32	−10.72
ALT 23	15.63	−10.61	−10.60	−10.16
ALT 24	17.00	−11.49	−8.58	−12.46

4.4. Modelling for future uncertainty in demand growth

Now that a methodology to better satisfy multiple environmental objectives has been demonstrated, the issue of uncertainty needs to be addressed within a multi-objective framework. This will be done using stochastic programming with recourse (as described in Section 3.4) to include flexibility to uncertainty in demand growth.

The deterministic model was adjusted to a two-stage stochastic model by allowing different demand futures to unfold. The futures were split after the decision node to represent the low, medium and high demand forecasts published in the NIRP [47]. These forecasts are presented in Table 3.

Table 3
Demand scenarios for various futures [47]

Demand scenario	2002 (PJ)	2021 (PJ)
Low	666	837
Medium	666	1055
High	666	1209

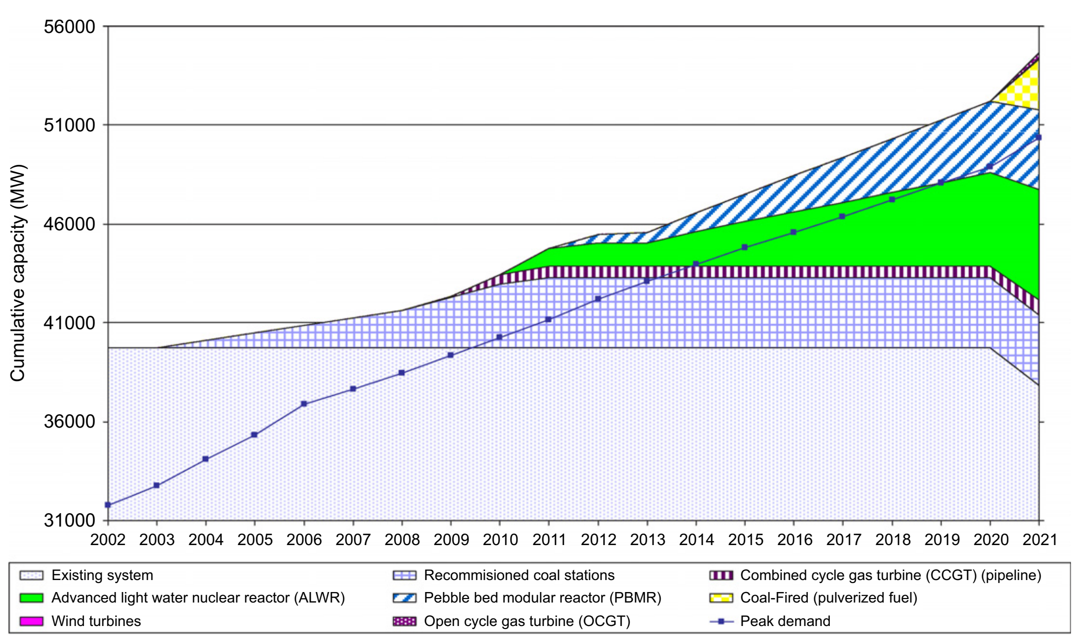

Fig. 3. Technology capacity summary for Alternative 11.

As a demonstration of the methodology, the decision node was positioned early in the time horizon (2009) to address the possibility of demand growth uncertainty as soon as possible, but to also allow time for the model to hedge for demand growth risk given the technology lead times involved. Investments for major new technologies were split into their ODC and EPC components to account for technology lead times, and to include an element of real options theory into the analysis. The timing of the decision node is itself a variable, whose influence could be explored via a parametric sensitivity study. This is not undertaken here.

Two versions of the stochastic model were run: one to yield the "naïve" solution and the other to yield the "hedged" solution. In the "naïve" model, the medium demand scenario was given a 99.8% probability of occurrence so that no hedging would be done for the alternate demand futures (see Section 3.4.3). In the hedged model, each demand profile was given an equal probability of occurrence[16] to explore the possible hedging that could be done for demand growth uncertainty. The reduced set of scenarios used previously to generate the deterministic solutions (which included PGPs to better satisfy multiple objectives) were then rerun in a stochastic version of the model to generate the naïve and hedged stochastic solutions. The alternatives' numbers used for the stochastic model runs correspond to the sets of PGPs used previously in the deterministic model runs.

The hedged solution was then compared to the naïve solution for each alternative to calculate the ECIU under all attributes. The results are shown in Table 4 which indicates the difference between the naïve and hedged solutions. Positive values indicate that the hedged solution had lower values (i.e. costs, CO_2-eq emissions, SO_2-eq emissions or water consumption) than the naïve solution hence indicating a positive cost for ignoring uncertainty.

It can be seen in Table 4 that the ECIU can be either positive or negative for any of the attributes individually; however, no naïve solution ever outperforms the hedged solution in all attributes simultaneously. This occurs because the model is attempting to hedge for multiple objectives and there is compensation occurring in the hedging process between the performances in the different criteria. This compensation is directly affected by the values of the PGPs as they inform the extent to which each attribute is contributing to the overall value of the objective function (i.e. overall discounted system cost). Therefore, for a given set of PGPs, the model may find it optimal to reduce one attribute at the expense of another as long as the overall objective function is minimised in the process. It can therefore be said that the hedging process is consistent with the overall multi-objective framework as it too is informed by the value of the PGPs to the extent to which the non-cost criteria should be considered in the optimisation.

[16]Sensitivity analyses can be done on the probabilities assigned to each state of the world, in order to determine the effect that the probabilities have on the solutions. This is not illustrated here, but would be important to do to generate defensible plans.

Table 4
Expected cost of ignoring uncertainty for each attribute

Alternative	Cost difference (Million ZAR)	CO_2-eq difference (Million ton)	SO_2-eq difference (Thousand ton)	Water consumption difference (Million ton)
BASE	1400	−4	−15	10
ALT 1	1400	−4	−15	11
ALT 2	1400	−4	−4	13
ALT 3	−900	3	34	37
ALT 4	−400	2	24	24
ALT 5	600	1	10	15
ALT 6	700	0	−16	9
ALT 7	1800	−3	−16	8
ALT 8	1500	−5	−21	10
ALT 9	−100	8	−20	38
ALT 10	800	3	−104	35
ALT 11	−200	−6	−3	32
ALT 12	1400	−4	−41	16
ALT 13	1900	−5	−14	6
ALT 14	1500	−5	−15	14
ALT 15	2600	−9	−30	16
ALT 16	−900	3	34	28
ALT 17	2000	−6	−28	7
ALT 18	−1600	14	23	24
ALT 19	−500	4	34	31
ALT 20	2300	−14	19	3
ALT 21	1900	1	−6	19
ALT 22	2600	−17	−12	13
ALT 23	−200	8	−80	46
ALT 24	−2400	17	−125	89

To illustrate what hedging for demand growth uncertainty may imply for technology selection, the investments in Pebble bed modular reactor (PBMR) and Combined cycle gas turbine (CCGT) technologies for Alternative 11 for the hedged and naïve stochastic demand scenarios are compared in Tables 5 and 6.

It can be seen that the hedged solution invests in more CCGT and less PBMR before the decision node in 2009 than the naïve solution. This is due to the fact that, when ignoring uncertainty, and therefore assuming that all ODC investments will lead to EPC investments, it is cheaper to invest in PBMR than in CCGT, within the limits of information currently available on PBMR. However, when demand uncertainty is taken into account, and it is no longer assumed that all ODC investments will be followed by EPC investments, it becomes cheaper to invest in more CCGT initially (getting it "investment ready") to hedge against uncertain demand profiles because of the far lower ODC component of the CCGT investment compared to PBMR. This initially increased investment allows for investment in larger amounts of CCGT after the decision node in the hedged solution, whereas the naïve solution is limited to building less CCGT. This contributes to the

Table 5
Excerpt from investment summary for hedged stochastic solution for Alternative 11

Demand scenario	Hedged solution (MW)					
	Pebble bed modular reactor			Combined cycle gas turbine (LNG)		
	Low	Medium	High	Low	Medium	High
Phase 1 ODC						
2002	–	–	–	–	–	–
2003	–	–	–	–	–	–
2004	–	–	–	–	–	–
2005	–	–	–	–	–	–
2006	–	–	–	–	–	–
2007	–	–	–	–	–	–
2008	3080	3080	3080	9500	9500	9500
Phase 2 EPC						
2009	0	0	0	0	0	767
2010	0	0	0	0	0	0
2011	0	0	0	0	0	427
2012	0	440	440	0	0	0
2013	0	440	440	0	0	0
2014	0	440	440	0	0	0
2015	0	440	440	0	0	835
2016	0	440	440	0	0	778
2017	0	440	440	0	0	796
2018	0	440	440	0	0	827
2019	0	0	0	0	705	1515
2020	0	0	0	0	1325	1626
2021	440	0	0	0	1935	1935
Total	440	3080	3080	0	3960	9500

Table 6
Excerpt from investment summary for naive stochastic solution for Alternative 11

Demand scenario	Naive solution (MW)					
	Pebble bed modular reactor			Combined cycle gas turbine (LNG)		
	Low	Medium	High	Low	Medium	High
Phase 1 ODC						
2002	–	–	–	–	–	–
2003	–	–	–	–	–	–
2004	–	–	–	–	–	–
2005	–	–	–	–	–	–
2006	–	–	–	–	–	–
2007	–	–	–	–	–	–
2008	3960	3960	3960	4175	4175	4175
Phase 2 EPC						
2009	0	0	0	0	0	738
2010	0	0	0	0	0	261
2011	0	0	0	0	0	427
2012	0	440	440	0	0	203
2013	0	440	440	0	0	220
2014	0	440	440	0	0	803
2015	0	440	440	0	0	745
2016	0	440	440	0	0	752
2017	0	440	440	0	0	26
2018	0	440	440	0	0	0
2019	0	440	440	0	305	0
2020	0	0	440	0	1935	0
2021	440	440	0	0	1935	0
Total	440	3960	3960	0	4175	4175

hedged solution being cheaper than the naïve solution as well as having lower water consumption levels as can be seen in Table 4. It does, however, also contribute to the hedged solution having higher CO_2-eq and SO2-eq emissions due to the increase use of gas instead of nuclear power. It must be noted, however, that the hedged solution for Alternative 11 still resulted in an increase in total discounted system cost of 4.21% relative to the *base case*,[17] and a decrease in CO_2-eq emissions of 5.47%, a decrease in SO_2-eq emissions of 5.52% and a decrease in water consumption of 5.48% all relative to the *base case*.

As an example, retrospective analysis of Alternative 11 yields PGP values of 38.68 ZAR/ton CO_2-eq, 0 ZAR/ton SO_2-eq and 0 ZAR/ton H_2O. The PGP values could s imply be translated into an equivalent (and appropriate) tax. For example, a carbon tax in this case would be 38.68 ZAR/ton CO_2-eq emitted. Equally this could be expressed in terms of a tax per unit of electricity generated by station type (e.g. 0.13 c/kWh for a new coal-fired station for this system).

[17]The base case referred to in this section is the least-cost solution (no PGPs) using the hedging model.

Including PGPs into a stochastic programming model with recourse and splitting investments into their ODC and EPC components thus yields solutions that improve on the corresponding *naïve solutions* on the basis of multiple objectives defined by the PGPs while still better satisfying the non-cost objectives relative to the *base case* scenario.

5. Conclusions

This paper has demonstrated that a partial equilibrium optimisation framework can be extended to include multiple environmental objectives through the addition of Pareto generation parameters (PGPs) introduced into the optimisation in the form of cost penalties. This forces the optimisation routine to find solutions that attempt to satisfy multiple objectives. It is an efficient method for extending the analysis to multiple objectives as the solutions generated are non-dominated and are generated from ranges of performances in the various criteria rather than from arbitrarily forcing the selection of particular technologies. Extensive sections of the non-dominated solution space can be generated and later screened to allow further, more detailed exploration of areas of the solution space.

This paper has also demonstrated that this analysis can be extended to include uncertainty in demand growth through stochastic programming with recourse. By splitting new power station investments into ODCs and EPC phases, the concept of technology lead times can be accounted for in light of a decision node in the time horizon. The hedging that is done in the recourse programming is automatically translated from purely financial to include whatever attributes the PGPs represent, due to the cost penalties that the PGPs impose on the solutions. The hedged solutions improve on the naïve solutions under the multiple criteria considered as well as better satisfy the non-cost objectives relative to the base case.

This methodology provides a framework for policy makers to generate a solution set for the power expansion problem that represents a range of solutions that each satisfies multiple objectives to a varying extent. The solutions also have built-in flexibility to demand growth uncertainty. The set of solutions generated in this manner can be used as part of a transparent decision making process in which policy maker preferences can ultimately inform the selection of a preferred solution. They also give policy makers an indication of the appropriate market signals necessary to influence the market towards a preferred state. This would be done retrospectively from the preferred solutions, through an analysis of the PGP values used to generate those solutions.

6. Further development of the methodology

The approach presented here could readily be modified to a mixed integer programming approach so as to model power station investments in technologically consistent blocks rather than treating capacity as a continuous variable. The methodology has been extended to include an analysis of robustness in relation to data and fuel price uncertainty as well as uncertainty relating to decision maker preferences. Furthermore, to assist policy makers in the process of selecting preferred solutions from the extensive set of non-dominated solutions generated as described in this paper, a decision support framework based on multi-criteria decision analysis (MCDA) and scenario analysis has been developed [4]. This is part of our on-going research development [4,63]. As a whole, this would provide a holistic methodology for generating ESI expansion scenarios for multiple objectives, where the alternatives generated have inherent flexibility to demand growth uncertainty, as well as a framework for identifying preferred solutions under those objectives that are robust to data and fuel price uncertainties and are evaluated in light of uncertainty in decision maker preferences.

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Appendix

Parameter uncertainty information related to generation phase is given in Table 7 and the summary of cost and performance data for new supply-side options is given in Table 8.

MARKAL stochastic programming with recourse formulation:

$$\textit{Minimise} \quad Z = \sum_{w \in W(t)} \sum_{t \in T} C_{t,w} \bullet X_{t,w} \bullet p_{t,w}$$

$$\textit{subject to} \quad A_{t,w} \bullet X_{t,w} \geqslant b_{t,w} \quad \forall t \in T, \ \forall w \in W(t), \tag{8}$$

where

t is the time period
T the set of time periods
t^* the resolution time
w the outcome index (state of the world)
$W(t)$ the set of outcome indices for time period t. For all t prior to resolution time t^* $W(t)$ has a single element (stage one). For $t \geqslant t^*$, (t) has multiple elements (stage two)
$X_{t,w}$ the column vector of decision variables in period t, under scenario w
$C_{t,w}$ the cost row vector in time t under scenario w
$p_{t,w}$ the probability of scenario w in period t; $p_{t,w}$ is equal to 1 for all t prior to t^* and $\sum_{w \in W(t)} p_{t,w} = 1$ for all t
$A_{t,w}$ the coefficient matrix (single period constraints) in time period t, under scenario w
$b_{t,w}$ the right-hand side column vector in time period t, under scenario w.

Table 7
Parameter uncertainty information relating to generation phase

Parameter	Type of uncertainty	Data representation	Generic approach to uncertainty
Non-technology specific parameters			
Reserve margin	Technical model parameter[18]	Decided by NIRP advisory review committee	Scenario analysis (within generation phase)
Discount rate	Technical model parameter	Decided by NIRP advisory review committee	Settled by expert agreement although could be explored using scenario analysis
Time horizon	Technical model parameter	Decided by NIRP advisory review committee	Settled by expert agreement
Emission equivalent conversion factors	Technical model parameter	Inter-Governmental Panel on Climate Change (IPCC) characterisation factors [59] for the direct global warming potential and the (Danish) Environmental Design of Industrial Products (EDIP) effect factors [60] for acidification potential	Different methods would yield slightly different results for the effects depending on the modelling assumptions used for each method. A sensitivity analysis could be done using different methods to determine their effect
Demand shape	Technical empirical parameter[19]	Based on NIRP data	Scenario analysis could be used to explore the effect of different demand shapes if this was of interest and relevance to the particular case study
Demand forecast	Technical empirical parameter	Taken from NIRP data for low, median and high demand values	Two-stage stochastic programming could be used to hedge for demand growth uncertainty. Alternatively scenario analysis could be used to evaluate different demand scenarios
Demand probabilities	Technical model parameter	Modeller-defined values	Scenario analysis (within generation phase)
Demand uncertainty resolution date	Technical model parameter	Modeller-defined	Scenario analysis (within generation phase)
Standard technology parameters that go into options generator			
Investment cost	Technical empirical parameter	Adjusted mean value taken from NIRP literature survey on international values	Parametric sensitivity analysis within generation phase or error propagation/robustness analysis outside of options generation phase. Alternatively stochastic programming with recourse could be used to hedge for uncertainty if it was found that it was significant for this parameter

Table 7 (*continued*)

Parameter	**Type of uncertainty**	**Data representation**	**Generic approach to uncertainty**
Generation costs (O&M)	Technical empirical parameter	Adjusted mean value taken from NIRP literature survey on international values	Parametric sensitivity analysis within generation phase or error propagation/robustness analysis outside of options generation phase. Alternatively stochastic programming with recourse could be used to hedge for uncertainty if it was found that it was significant for this parameter
Emission coefficients	Technical empirical parameter	Adjusted mean value taken from NIRP literature survey on international values	Parametric sensitivity analysis within generation phase or error propagation/robustness analysis outside of options generation phase. Alternatively stochastic programming with recourse could be used to hedge for uncertainty if it was found that it was significant for this parameter
Availability factor	Technical empirical parameter	Decided by NIRP advisory review committee (based on World Energy Council best quartile results 2003)	Settled by expert agreement
Thermal efficiency	Technical empirical parameter	Adjusted mean value taken from NIRP literature survey on international values	Settled through expert opinion/literature survey. Parametric sensitivity analysis can be done in the options generation phase to explore the effect of uncertainty in this parameter
Fuel cost	Technical empirical parameter	Values taken from NIRP	Parametric sensitivity analysis within generation phase or error propagation/robustness analysis outside of options generation phase. Alternatively stochastic programming with recourse could be used to hedge for uncertainty if it was found that it was significant for this parameter
Plant lead times	Technical model parameter	Values taken from NIRP	Expert agreement or scenario analysis in the generation phase
Plant lifetime	Technical model parameter	Values taken from NIRP	Settled by expert agreement
Pareto generation parameters	Technical model parameter	Case study relevant and stakeholder/modeller-defined range chosen	Extensive range of values used to generate a representation of the non-dominated solution space surface
Station type (peaking, mid-merit, base load)	Technical model parameter	Taken from NIRP	Settled by expert agreement
Annual investment limit	Technical model parameter	Values taken from NIRP	Settled by expert agreement
Total investment limit	Technical model parameter	Values taken from NIRP	Settled by expert agreement

[18]Technical model parameters refer to parameters in the model that are chosen by the modeller or decision maker to represent the problem at hand.
[19]Technical empirical parameters are parameters that have real values such as costs, emission coefficients and efficiencies.

Table 8
Summary of cost and performance data for new supply-side options (taken directly from NIRP [47])

	Type of station	No. of units	Station size (MWSO^{-})	Unit size (MWSO)	Lifetime (Years)	Overnight capital		PV capital (10%) (R/kW)	EPC lead (Years)	Fixed O&M (R/kW/a)	Variable O&M (R/MWh)	Fuel price	Efficiency (HHV) (%)
						Rm	R/kW						
New coal-fired plants												R/ton	
CF Dry + FGD	Non-peaking	6	3850	642	30	37 723	9799	12 324	4	125.28	7.51	60	34.59
Pumped storage													
Pumped storage (Braamhoek public data)	Peaking	4	1330	333	40	4200	3158	5179	7	90.00	9.00		76.00
Pumped storage (generic)	Peaking	3	998	333	40	7182	7200	8857	7	90.00	9.00		76.00
Gas turbines												R/GJ	
CCGT (without trans benefits) pipe	Non-peaking	5	1935	387	25	9797	5063	5659	3.0	175.26	10.58	20	47.04
CCGT (with trans benefits) pipe	Non-peaking	5	1935	387	20		4405	4925	3.0	156.48	9.45	20	47.04
CCGT (without trans benefits) LNG	Non-peaking	5	1935	387	25	9797	5063	5659	3.0	175.26	10.58	32	47.04
CCCT (with trans benefits) LNG	Non-peaking	5	1935	387	25		4405	4925	3.0	156.48	9.45	32	47.04
GT-Open Cycle (kerosene)	Peaking	2	240	120	25	920	3833	3949	2.0	79.80	65.88	72	32.26
GT-Open Cycle (LNG)	Peaking	2	240	120	25	920	3833	3949	2.0	79.80	65.88	32	32.26
GT-Open Cycle (Local syngas)	Peaking	2	240	120	25	920	3833	3949	2.0	79.80	65.88	28	32.26
GT-Open Cycle (LPG)	Peaking	2	240	120	25	920	3833	3949	2 0	79.80	65.88	56	32.26
New FBC												R/ton	
Greenfield FBC	Non-peaking	2	466	233	30	4508	9669	11 511	4.0	204.61	19.54	10	36.65
Imports													
Imported hydro	Non-peaking	4	1200	300	30	17 044	14 203	19 948	6.5	204.88	0.00	n/a	n/a
Renewables													
Solar thermal	Peaking	3	300	100	30	10 043	33 477	34 589	3.0	147.29	0.13	0	n/a
Wind	Peaking	20	20.00	1	20	154	7714	7768	2 0	167.02	0.00	0	n/a
Nuclear												R/MWh	
PBMR (1st MM incl. trans benefits)	Non-peaking	8	1320	165	40		16 533	17 340	4	157.65	6.75	45	40.54
PBMR (1st MM excl. trans benefits)	Non-peaking	8	1320	165	40	24 693	18 707	19 651	4	157.65	6.75	45	40.54
PBMR (Series MM excl. trans benefits)	Non-peaking	8	1364	171	40	14 678	10 761	10 853	4	161.20	6.75	45	44.50
PWR (incl. trans benefits)	Non-peaking	2	1747	874	40	27 944	15 995	15 139	4	507.22	0.00	45	31.48
PWR (excl. trans benefits)	Non-peaking	2	1747	874	40	25 389	14 532	15 290	4	507.22	0.00	45	31.48

MWSO: capacity sent out (after own use has been taken into account).

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