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A review of approaches to uncertainty assessment in energy system optimization models

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ABSTRACT

Energy system optimization models (ESOMs) have been used extensively in providing insights to decision makers on issues related to climate and energy policy. However, there is a concern that the uncertainties inherent in the model structures and input parameters are at best underplayed and at worst ignored. Compared to other types of energy models, ESOMs tend to use scenarios to handle uncertainties or treat them as a marginal issue. Without adequately addressing uncertainties, the model insights may be limited, lack robustness, and may mislead decision makers. This paper provides an in-depth review of systematic techniques that address uncertainties for ESOMs. We have identified four prevailing uncertainty approaches that have been applied to ESOM type models: Monte Carlo analysis, stochastic programming, robust optimization, and modelling to generate alternatives. For each method, we review the principles, techniques, and how they are utilized to improve the robustness of the model results to provide extra policy insights. In the end, we provide a critical appraisal on the use of these methods.

1. Introduction

Energy models can be categorized in various ways [1]. A comprehensive review by Jebaraj and Iniyan [2] on existing energy models in 2006 classifies energy models into energy planning models, energy supply–demand models, forecasting models, renewable energy models, emission reduction models, and optimization models. Gargiulo and Ó Gallachóir [3] classify long term energy models based on underlying methodology (simulation, optimisation, economic equilibrium), analytical approach (top-down, bottom-up, hybrid [4]), and sectoral coverage (energy system [5], power system [6]).

As an important branch of energy models, energy system optimization models (ESOMs) can be characterised as technology-rich, optimization models covering an entire energy system. ESOMs have been widely used to offer critical climate and energy policy insights at national, global, and regional scales [7]. These models provide an integrated, technology-rich representation of the whole energy system for analysing energy dynamics over a long-term, multi-period time horizon. Optimal solutions are computed using linear programming techniques. The results are used to explore the least cost energy system pathways for an energy secure and low carbon future, offering insights on energy transition, economic implications and environmental impacts. One of the widely used ESOM model is the MARKAL/TIMES family of models [8] developed and maintained by the Energy Technology Systems Analysis Programme (ETSAP) under the aegis of the International Energy Agency (IEA) since the 1970s. Other ESOM models include MESSAGE [9], ESME [10], OSeMOSYS [11] and TEMOA [12]. The schematic of a typical ESOM model is shown in Fig. 1. The model inputs including energy supply, energy demand and associated economic parameters are shown on the sides, and the model outputs are shown on the top and bottom.

While models are becoming increasingly more complex and sophisticated, projecting 50 or 100 years into the future is inherently uncertain [13]. Edenhofer et al. [14] categorizes uncertainties into parametric and structural. *Parametric* uncertainties arise due to lack of knowledge about empirical values associated with model parameters, and *structural* uncertainties refer to uncertainties in the model equations that collectively define the model structure - examples of the latter include the default ESOM formulation that ignores the heterogeneity among decision makers in the energy system, the manner in which non-

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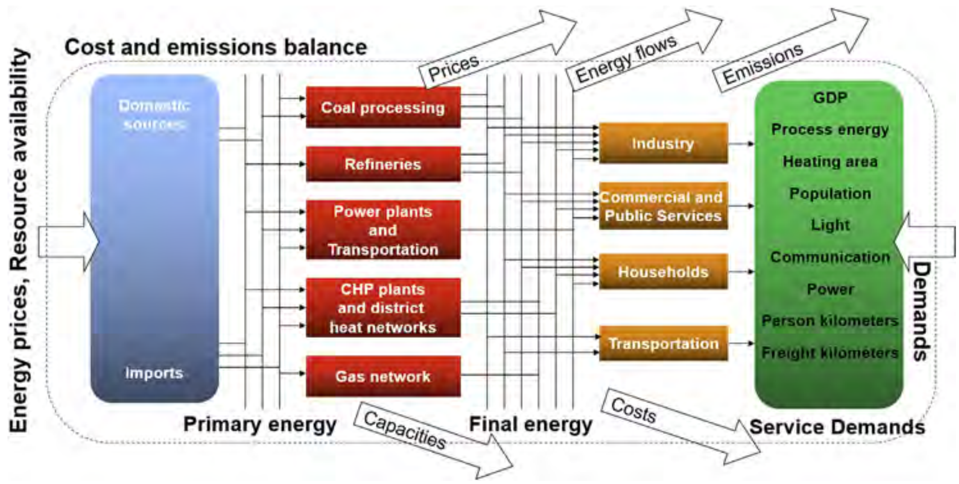

Fig. 1. Schematic of TIMES model [27].

economic considerations factor into energy purchasing decisions, and the role that politics, social norms, and culture play in shaping public policy. Due to model complexity, computational intensity, and the time pressure to produce relevant policy, many ESOMs have been used in a deterministic fashion with limited attention paid to uncertainty. A review of energy system models by Pfenninger points out that assessing uncertainties has become one of the major challenges of ESOMs [15]. When formalizing best practices for using ESOMs, DeCarolis et al. [16] highlight the importance of quantifying uncertainties. Ignoring uncertainty is problematic as many of the issues that ESOM analyses consider are deeply uncertain. They can be described as belonging to the area of "post-normal science" [17], where both the uncertainties and the decision stakes inherent in these issues are high. As Lempert [18] points out, the long-term policy analysis conducted with ESOMs requires decision making under *deep uncertainty*, where analysts and decision makers do not know or agree on (1) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes (i.e. as they correspond to different policy objectives). This underlines the importance of modelers carrying out uncertainty analysis in a more systematic way to improve the robustness of model outputs and their use for providing policy insights. By systematic, we mean analysis that applies a formal approach to a broad range of uncertainties, and which explicitly addresses the three aspects of *deep uncertainty* in order to provide additional policy insights beyond simple scenario analysis.

It is informative to survey the types of methods available for undertaking uncertainty assessments in different types of energy, economy, environment, and engineering (E4) models, for which a number of reviews have been undertaken. Energy models are designed with different end uses and research problems in mind. Due to the differences in model paradigm and analytical approach across various models, the uncertainty techniques available for each type of model vary. Several existing reviews focus on certain types of models, such as integrated assessment models [19–21], optimization models [22], power systems models [23], environmental models [24], or energy related issues such as climate change [25] and sustainable energy planning [26].

Given an expectation of increased global efforts to limit global warming to well below 2° after the adoption of the Paris Agreement, ESOM models are likely to become critical tools that can supply an evidence base for governments, research institutions and international organizations exploring future pathways to deep decarbonization of energy systems. Therefore, it is necessary to target specifically on ESOMs and undertake a comprehensive review of the literature to identify the application of uncertainty methods. The review was done systematically, using a pre-defined search strategy. We identified four main techniques that have been applied, including Monte Carlo analysis (MCA), Stochastic Programming (SP), Robust Optimization (RO), and modelling to generate alternatives (MGA). Besides introducing the principles and formulations of each technique, the paper focuses on discussing how the different techniques are applied to provide additional policy insights that cannot easily be obtained from deterministic scenario runs. We also provide an appraisal and recommendations on the choice of uncertainty techniques according to the policy issue and the types of uncertainty in question. This paper is organized as follows. In Section 2, we present the literature search methodology carried out. Section 3 thoroughly reviews the four uncertainty techniques. Section 4 provides a brief discussion and concluding remarks.

2. Literature search

To capture the relevant literature on uncertainty analysis in ESOMs we carried out a systematic literature search using a three-phase search strategy based on the techniques described in [28].

The first phase was a broad literature search for all primary studies possibly relevant to the research question using the electronic database engines Scopus and ScienceDirect. The search terms used were grouped into two lists as shown in Table 1. The first list includes keywords associated with ESOMs, and the second list includes those related to uncertainty. The actual search strings applied were obtained by connecting two keywords from both lists with the Boolean "AND". The search terms contained both generic search terms and specific terms. Generic terms such as "uncertainty", "stochastic" and "energy modelling" ensured a wide set of result coverage without missing key studies. More specific search terms were identified from previous search results and included model names such as "MARKAL" and "ESME", as well as uncertainty techniques like "Monte Carlo analysis" and "stochastic

Table 1
Search term lists for literature search.

Energy Model Related	Uncertainty Related
Energy system model	Uncertainty
Energy systems	Stochastic
Energy modelling	Sensitivity analysis
Energy modeling	Monte Carlo analysis
MARKAL	MGA
TIAM	Stochastic programming
ESME	Robust optimization

programming". Combining the two search term lists resulted in 42 search strings (e.g. "uncertainty and energy modelling", "Monte Carlo Analysis and MARKAL"). Search strings were searched for in titles, keywords, and abstracts. The aggregated number of results from both electronic databases totalled over 2100.

The second phase was to apply a filter on the initial search results to exclude studies unrelated to ESOM type models i.e. comprehensive pan-sectoral tools which address trade-offs through time and the transformation of whole energy systems towards sustainability. The search terms we applied are relatively generic and have been used extensively in many subject areas. For example, the term "energy system" may refer to specific sectoral models exploring building systems, power transmission systems or energy distribution systems (e.g. gas networks). We filtered the results based on a case-by-case review of individual titles and abstracts to rule out studies unrelated to ESOM models.

In the third phase, we closely examined the remaining studies, and selected studies under review according to the following criteria:

i. First, the study explicitly addresses uncertainty as a core part of analysis.
ii. Second, the energy system model used is an ESOM model covering the entire energy system, and simulation models like LEAP [29] and power systems models like PLEXOS [30] were excluded.
ii Third, the uncertainty analysis is carried out in a systematic manner using formal techniques that are documented by the authors.

As the electronic databases used in our initial search may not have covered all relevant studies, we also searched the reference lists from relevant papers to look for publications that could have been missed by the academic search engines.

As shown in Fig. 2, from the literature search, we found over 100 studies that featured scenario analysis using deterministic scenarios, and only 34 studies applying formal uncertainty techniques, including MCA (9 studies), stochastic programming (18 studies), robust optimization (3 studies), and modelling to generate alternatives (4 studies).

3. Systematic review

The literature search shows that only a minority of ESOM-based studies apply systematic formal approaches to address uncertainties in long-term energy pathways. The majority of ESOM studies use small-ensemble scenario analysis and simple sensitivity analysis to handle uncertainties, where a base case scenario is created, and then the impacts of uncertain policy instruments or exogenous conditions are analyzed through alternative scenarios with additional constraints and assumptions. For example, Cabal et al. [31], Calderón et al. [32], and Føyn et al. [33] applied additional climate policy constraints in emission targets and carbon taxes. Comodi et al. [34], Grah et al. [35] made alternative technological assumptions in technology efficiencies and technology costs. Gracceva and Zeniewski [36] constrained resource potential on the supply side. Chiodi et al. [37] compared a number of sustainable bioenergy scenarios. Czyrnek-Delêtre M.et al. [38] assessed the impacts of including indirect land use change on mitigation pathways. Balash et al. [39], Borjesson et al. [40], Densing et al. [41], Gritsevskyi and Schrattenholzer [42], and Fortes et al. [43] constructed alternative scenarios by varying assumptions in different aspects of the model. The alternative scenarios are sometimes accompanied with sensitivity analysis in a "one-factor-at-a-time" (OAT) fashion, where certain parameters are varied a few times while the other assumptions are held constant. For example, sensitivity scenarios across a range of studies are carried out by varying EV battery costs [44], emission constraints [45,46], and discount rate [47]. The above examples are typical of the kind of approaches to uncertainty analysis that are commonly found in the ESOM literature.

As a simple method to implement and communicate, scenario analysis with a small-ensemble of cases has played a significant role in providing policy insights in future years through exploring a spread of narrative-based what-if scenarios, and has been critical in informing policies to date on cost effective pathways towards an energy secure [48] and low carbon [49] [50] future. On the other hand, due to a number of limitations, this simple approach has received many criticisms. Usher and Strachan [51] argued that deterministic methodology is not suitable for complex and multi-faceted problems with inherent uncertainties. Trutnevyte et al. [52] pointed out that simple deterministic approaches to modelling often do not anticipate real world developments in the energy system. Morgan and Keith [53] argued that scenarios with detailed storylines underestimate the range of possible outcomes and lead to cognitive bias, which make them appear more probable and plausible than they are in actuality. To improve the use of scenarios for tackling uncertainties and informing decision making, many authors have suggested innovative techniques [52,54–57], for example designing scenarios to capture a wide range of uncertainties while subsequently selecting a small subset of policy relevant scenarios.

3.1. Monte Carlo analysis

3.1.1. Principle

Compared to scenario and sensitivity analysis, Monte-Carlo Analysis

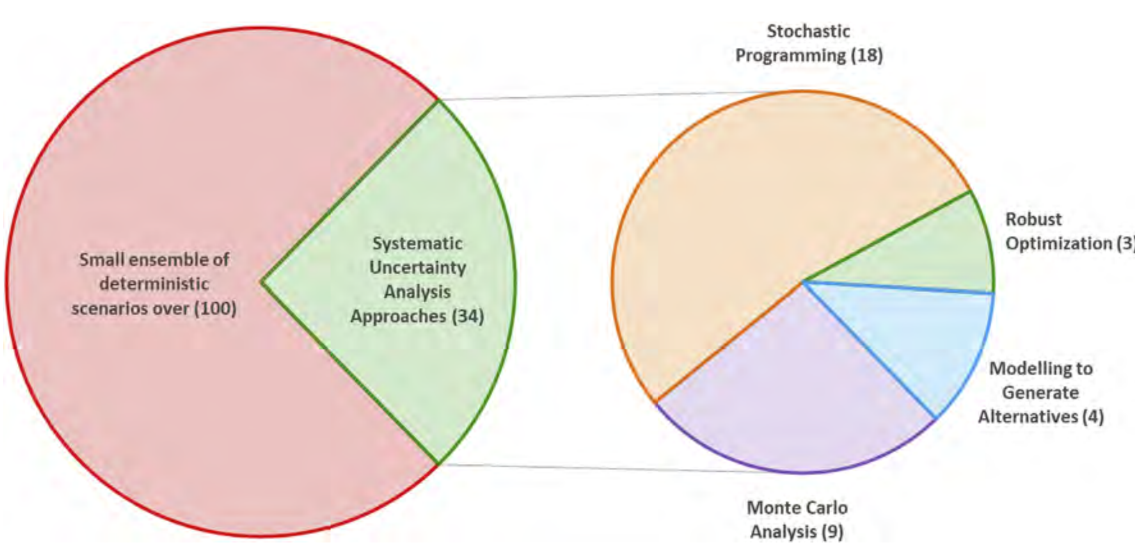

Fig. 2. Number of ESOM studies that address uncertainties based on our literature search in 2017.

(MCA) is a more systematic way to address parametric uncertainties. The principle of MCA is to propagate uncertainties by simultaneously perturbing multiple uncertain input parameters represented by probability distributions. The collection of model outputs can be evaluated statistically using a global sensitivity analysis (GSA) approach [58,59], which can be defined as how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input. Saltelli and Annoni [60] proves the statistical inadequacy of the "OAT" approach with a geometric approach and point out that GSA is a better practice in sensitivity analysis.

Carrying out a Monte Carlo simulation generally requires the following steps.

1. Assign probability distributions to multiple exogenous variables
2. Generate a sample of random values
3. Feed the sample into the model to compute a set of outputs
4. Iterate the procedure N times and collect N samples of model outputs
5. Evaluate sets of outputs using statistical techniques

The probability distributions are usually obtained through modelers' judgement or expert elicitations. For example, in some studies [61] and [62] the uncertain parameters are assumed to vary within a certain range across the deterministic values in the base case scenarios. In another [63], the results from expert elicitations are aggregated to determine input range and probability distributions. In addition, the interdependencies between inputs can be defined by covariance [64].

Once probability distributions are assigned to inputs, the model is then run multiple times using one set of inputs for each run. Typically, one hundred to several hundred runs are considered sufficient, but the number could also be determined statistically. Generally, the number of runs required is independent of the number of uncertain parameters, and mainly depends on the level of confidence. For example, in [65] Alzbutas and Norvaisa applied Wilks' formulas [66], and determined that 93 runs are required to ensure an observation has a 95% probability (u = 95%) to fall within the two sided 95% confidence interval (v = 95%) of output distribution, where n1 and n2 are the required number of runs for one-sided and two sided tolerance limits respectively:

$$n_1 \geq \ln(1-v)/\ln(u)$$

$$n_2 \geq (\ln(1-v) - ln((n_2/u) + 1 - n_2))/\ln(u)$$

Morgan's formula [67] is used by Pye et al. [68], where c is the deviation enclosing the 95% confidence interval, s is the sample standard deviation, and w is the requisite confidence interval width. The calculation showed that 475 runs are required to estimate the sample mean with less than 1% error:

$$n > \left(\frac{2cs}{w}\right)^2$$

3.1.2. Applications

In our literature search, we found 9 studies that perform uncertainty analysis through MCA. The research question, assumptions and key insights gained in each study are summarized in Table 3, As a computational intensive method, MCA method did not become widely feasible for ESOM models until the rapid development of computing power in the early 2000s. Seebregts et al. [69] first proposed its application for use with ESOMs, and De Feber et al. [70] later demonstrated its feasibility in MARKAL. The key policy insights delivered by an MCA may include the likelihood in reaching a particular policy target, which technologies are more robust in an uncertain future, and insights into the relationships between the model inputs and outputs.

One such application explored how system uncertainties might affect whether a specific carbon price level may or may not deliver emission reductions in the longer term. With the stochastic UK energy system model ESME, Pye et al. [68] found that 42% of runs failed to deliver the 80% carbon reduction target in 2050 at the reference carbon price of £421/t CO_2. The uncertainty can be mitigated by increasing the carbon price. A £30/tCO_2 increase in carbon price ensures a 100% probability in reaching the 2030 target, while controlling the probability to meet the 2050 target requires much larger carbon price increases.

Table 2
Commonly used acronyms for stochastic programming.

Full Name	Acronym
State of the world	SOW
Minimax regret criterion	MMR
Expected value of perfect information	EVPI
The cost of ignoring uncertainty	ECIU
Expected loss	EL
value of the stochastic solution	VSS
value of policy coordination	VPC

The results can also be used to identify the most robust technologies under uncertainty. High penetration over a wide range of outcomes is a strong indication of robustness. A technology can then be categorized as a "no hoper", a "marginal contender" or a "no regret option" [10]. Yeh et al. [71] analyzed the economic viability of hydrogen fuel cell vehicles. By plotting histograms of output distributions, it was determined that this technology is not viable in general as it has some level of penetration only in 6.4% of all simulations. The characteristics of the runs in which this technology is deployed demonstrated that this technology can be viable if its cost is reduced and oil prices and competing vehicle technology costs become higher. Lethtveer and Hedenus [62] explored the role of nuclear technologies in climate mitigation cost reduction. The histogram of MCA result shows that compared to conventional nuclear technologies, investing in advanced nuclear is more likely to achieve higher cost savings.

Linear optimization models like ESOMs are often criticized as "black-box" due to their lack of transparency [63]. Characterization of the relationships between inputs and outputs helps improve model transparency and unpacks the model structure. The scatterplot is a good starting point that provides visualization of the relationships between inputs and outputs. In [61], Hedenus et al. analyzed changes in energy supply and their effect on the deployment of transportation technologies. A scatterplot showed that battery cost strongly influences the electrification of road transportation. Electricity is used in the transport sector only if the battery cost is significantly reduced. However, it should be noted that the scatterplot approach is qualitative in nature (for interpretation of outputs) and requires human expertise to identify relationships [72].

To quantify the input-output relationships, GSA can be carried out using statistical methods such as regression analysis. For example, Johnson et al. [72] calculated correlation coefficients, where large correlation coefficients between a pair of inputs and outputs indicates a strong linear relationship. Bosetti et al. [63] carried out GSA to identify the key drivers of uncertainties and used the sign of change to determine whether the variation of one input parameter causes an increase or decrease in model output. Pye et al. [68] performed a multivariate linear regression and used standardized regression coefficients to rank the uncertain input factors. Biomass availability, gas prices and nuclear capital costs were identified as critical uncertainties for achieving emission reduction targets. In an analysis on the small and medium nuclear reactor viability in Lithuania, Alzbutas and Norvaisa [65] ranked the contribution of input parameters using partial correlation coefficients. The results showed that the discount rate has the strongest influence on the total system costs. Opposite to the modeler's expectation, the nuclear fuel price actually has the weakest influence on total system costs.

Table 3
Monte Carlo Analysis review summary.

Model	Research Question	Coverage and Time Horizon	Key Uncertain Inputs	Probability Distributions	# of Runs	Result Analysis	Key Policy Insights
MARKAL [70]	Incorporate technology learning mechanism into energy system	Western Europe All Sectors 2050	Progress ratios -solar PV -wind turbines	Uniform Triangular	100	Histogram	Progress ratios have high impacts on the success of wind and solar technologies.
GET 7.0 [61]	Impact of energy supply system on transport propulsion technologies	Global All Sectors 2100	Vehicle costs -Battery -Fuel cells -Gas storage	Normal	100	Scatterplot	Cost-effectiveness of propulsion technologies depend mainly on the relative price of energy carriers. Extreme vehicle costs have high impacts on the results.
GET [62]	The role of nuclear technology on climate mitigation cost reduction	Global All Sectors 2100	CCS capacity and costs Renewable costs and potential Gas and coal costs Nuclear technology costs Demands	Uniform	1000	Histogram	Employing nuclear technologies has potential to reduce climate mitigation costs. Compared to conventional technologies, investing in advanced nuclear technologies has greater climate costs reduction potential.
MARKAL [71]	Penetration of hydrogen fuel cell vehicle (H2-FCV) in US	US All sectors 2030	11 Parameters Fuel costs H2-FCV characteristics Other Vehicle characteristics	Uniform	500	Histogram Regression	H2-FCV is only viable with cost reductions, increased oil prices and increased costs of competing vehicle technologies.
MESSAGE [65]	Deployment of nuclear reactors in Lithuania	Lithuania All sectors 2025s	6 Parameters Nuclear Reactor characteristics	Uniform	100	Partial Correlation Coefficients	Constructing nuclear reactors is economically attractive. The discount rate has highest influence on total system cost, and the nuclear fuel price has the lowest influence
MARKAL [72]	Evaluate sensitivity in EPA's national MARKAL database and energy system model	US Electric Sector 2030	14 Parameters Fuel Costs Hurdle Rates Nuclear Capacity Renewable Growth Rates	Uniform	1000	Normalized linear regression	The main factor that influences the electricity sector is whether specific technologies and fuels meet base or peak load electricity demands
GCAM MARKAL_US WITCH [63]	Impact of technology uncertainties on a set of alternative environmental and economic metrics across models	Global & US All Sectors 2100	8 parameters Solar Nuclear Biofuel Bioelectricity CCS	LogUniform Uniform (Aggregated Expert elicitations and Importance sampling)	740 for each model	Global sensitivity measures (variance, density, CDF based) Sign of Change	Cost of nuclear energy affects emissions the most in unconstrained emission scenarios
ESME [68]	Impact of uncertainty on meeting UK decarbonization targets	UK All Sectors 2050	Investment costs Build rates Resource Availability Resource Prices	Triangular (Expert Elicitations)	500	Scatterplot Multivariate linear regression	The probability of meeting carbon reduction target is strongly dependent on the carbon price level. Biomass availability, gas prices and nuclear capital costs are critical uncertainties for achieving emission reduction targets.
PROMETHEUS [64]	Introduce the stochastic model PROMETHEUS	Global All sectors 2050	All parameters	Econometric method and expert judgement			

3.1.3. Limitations

Even though the MCA approach is not conceptually difficult and does not require modifications in model structures or mathematical formulations, performing MCA for ESOM models suffers computationally from a heavy computational burden. ESOM models generally have thousands of variables, and take much longer processing time compared to simulation models. Typical MCA requires at least hundreds of runs to guarantee uncertainty coverage, making it impractical for very large and complex models. Sampling techniques can be used to reduce the number of runs required for statistically significant results. For example, the Latin Hypercube Sampling technique [73] evenly samples from the probability distributions, and can be used to generate a relatively small sample set that represents the real variability. Importance sampling [74] techniques used by Bosetti et al. [63] sample from a different distribution and renormalize back to the original one. In this way, the areas of distributions with high interest but low probabilities can be sufficiently covered.

Another challenge for MCA is to obtain reliable probability distributions for uncertain inputs. The results from MCA can be very sensitive to distribution assumptions, and different distributions may give very different results even if they have the same mean and variance [75]. However, knowledge concerning the uncertainty of model inputs is often limited. It is unreliable to derive distributions based on historical data because many uncertainties in ESOM studies have a long term, and low frequency, and do not tend to occur repeatedly. Expert elicitation [76,77] can provide a foundation for assessing future uncertainties to support decision-making. It is important that expert elicitations to be carried out in a rigorous way and address the choice of expert, potential biases and overconfidence, convergence of different opinions, and trustworthiness in the results [78,79].

3.2. Stochastic programming

MCA is able to provide additional insights compared to conventional analysis, but each scenario is assumed equally likely and the results do not suggest a single best course of action. In addition, the model assumes that all future uncertainties are resolved at the current time with perfect foresight. This "learn now then act" approach diverges with reality since policy makers need to make decisions with uncertainties revealed only at a later time in an "act now then learn" fashion Sequential decision making using stochastic programming provides one single best course action that accounts for future uncertainties. The acronyms used in this section are provided in Table 2.

3.2.1. Principle

Stochastic programming considers multiple unresolved future uncertainties and determines optimal strategies by striking a compromise between the consequences of multiple ways of "guessing wrong" [80]. The stochastic result represents a hedging strategy that provides one single best course of "here and now" actions [81]. After the resolution time at which the actual values of uncertain parameters are revealed, the hedging strategy produces as many contingent strategies as the number of possible outcomes [82]. Each strategy is a recourse against the possible outcomes and the "wait and see" decisions can be made accordingly.

The formulation of the widely used *expected cost* criterion [83] can be illustrated in Fig. 3, which shows an event tree under uncertain carbon mitigation targets and energy prices. The model time horizon is divided into three time stages by two resolution times. The possible future outcomes in each stage are represented by branches known as "states of the worlds" (SOWs). The possible realizations of uncertain parameters are defined over the SOWs, while the deterministic parameters remain the same across all SOWs. The likelihood for each SOW is defined by the probability weightings shown along the branches. The optimal strategy is calculated by minimizing the expected value of total system cost over all SOWs using the formulation as shown below [83].

$$\textit{minimize} \sum_{s \in S(t)} \sum_{t \in T} C(t, s)^* X(t, s)^* p(t, s)$$

$$\textit{Subject to } A(t, s)^* X(t, s) \geq b(t, s)$$

- t = time period
- T = set of time periods
- s = SOW index
- S (t) = set of SOW index for time period t
- C(t,s) = cost row vector
- X(t,s) = decision variables
- p(t,s) = probability weightings
- A(t,s) = linear programming coefficient matrix
- b(t,s) = right hand side column vector

Anticipating a range of possible scenarios for analysis with stochastic programming is often possible, but it is difficult to reach a consensus on the likelihood of each outcome occurring. One common way to carry out the analysis under ignorance about the probability of future outcomes is to apply the Laplace expected cost criterion [80], which simply assigns equal probability weightings at each stage. Alternatively, the minimax regret criterion (MMR) can be applied [80]. The difference between the total system cost of the hedging strategy solution and the cost of the corresponding perfect foresight scenario is defined as the "regret". The stochastic programming formulation under MMR determines the hedging strategy by minimizing the total regret between the hedging strategy and all perfect foresight scenarios. Compared to the expected cost criterion, the results under MMR mainly depend on the extreme SOWs with highest and lowest values. This approach can thus be considered as a type of risk aversion technique.

Several metrics can be calculated to evaluate the uncertainties quantitatively. For example, the expected value of perfect information (EVPI) [51] represents the expected cost caused by uncertainty. It can also be interpreted as the expected cost savings if all uncertainties are removed and all future values are known with certainty right now. To calculate EVPI, the weighted average cost of the deterministic perfect foresight scenarios $Cost_{PFi}$ is calculated. Then the cost of the hedging strategy $Cost_{hedge}$ is determined using SOWs corresponding to the deterministic scenarios with the same set of probability weightings p_i. The cost of the hedging strategy is always higher than the weighted average cost of the deterministic scenarios since it poses one additional constraint, namely that only one pathway is allowed before the resolution time. The difference in the hedging strategy and the expected cost of the deterministic scenarios is the EVPI.

$$EVPI = Cost_{hedge} - \sum_{i}^{n} p_i Cost_{PFi}$$

The cost of ignoring uncertainty (ECIU) [81] estimates the cost of "guessing wrong". Suppose that the decision maker faces a number of J possible future outcomes each with probability p_j. Prior to the resolution time, the decision maker takes a naïve pathway, which simply assumes certain deterministic values for uncertain parameters. At the resolution time, the actual outcome j is revealed, and the decision maker needs to adjust his decisions by re-optimizing the pathway. The conditional cost of following the naive pathway and then adjusting the strategy based on the j^{th} outcome is $Cost_{j|\,naive}$. The ECIU is the difference between the total weighted conditional cost and the hedging strategy $Cost_{hedge}$.

$$\text{ECIU} = \sum_{j=1}^{J} p_j Cost_{j|\,naive} - Cost_{hedge}$$

The ECIU is also referred to as the expected loss (EL) metric [84] if the naïve strategy is to follow one of the J pathways from the beginning. The EL of following the k^{th} pathway until resolution is:

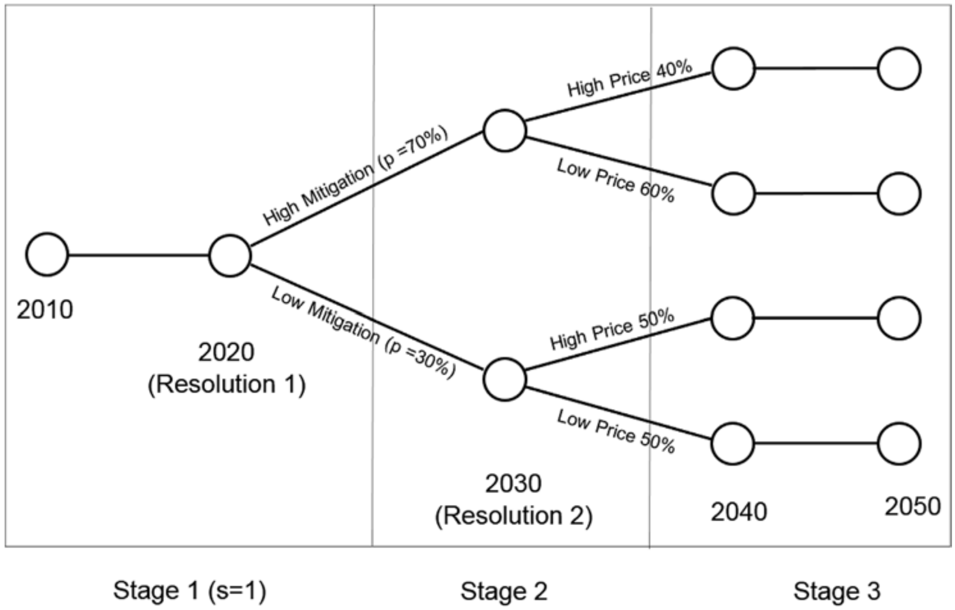

Fig. 3. Example of a three-stage Event Tree.

$$EL_k = \sum_{j=1}^{J} p_j Cost_{j|k} - Cost_{hedge}$$

Another metric similar to ECIU that measures the incremental cost of the stochastic solution is the value of the stochastic solution (VSS) [85], where the naïve strategy prior to the resolution date uses the expected values of the range of deterministic scenarios.

3.2.2. Applications

Stochastic programming was originally proposed by Dantzig [86] and later expanded by Wets [87] and Birge [85]. This approach has been applied widely after being incorporated into an enhanced version of MARKAL [87] and MESSAGE [89] in the 1990s and later in the TIMES model [83]. We have reviewed 21 stochastic programming studies with ESOMs, summarized in Table 4.

Besides providing a hedging strategy and recourse actions, most stochastic programming studies compare the trend of the hedging strategy and perfect foresight pathways, and conclude that the hedging strategy differs from all perfect foresight pathways. In addition, the hedging strategy does not represent the average or the interpolation of perfect foresight strategies, and always performs better in terms of system costs compared to a naïve approach that ignores future uncertainty. This implies that stochastic programming provides insights beyond deterministic scenarios.

Comparing hedging strategies and perfect foresight strategies also helps identify "super-hedging" actions, which are robust technologies that appear more in the hedging strategy than any of the perfect foresight strategies. For example, Labriet [90] analyzed global climate stabilization targets under uncertain GDP growth and temperature increase limits. Natural gas was identified as the most significant hedging strategy in China with 50% higher penetration in the hedging strategy than perfect foresight scenarios. Implementing gas is a "middle-of-the-road" pathway as it has moderate amount of emissions compared to other fossil fuels and relatively low capital costs compared to low-carbon options, and can be modified without severe economic consequences.

With the quantitative metric EVPI, Usher and Strachan [51] evaluated the costs of uncertainties in fossil fuel prices and biomass availabilities for the UK. The EVPI is very high under uncertain fossil fuel prices, indicating a very high cost of uncertainty. The high EVPI is mainly due to the difference in near-term actions chosen under the perfect foresight and hedging strategies. The uncertainty cost can be reduced by including novel mitigation options, which improves the flexibility of the energy system against changes in fossil fuel prices. The ECIU (or EL) is not as widely used as EVPI, but it quantifies the economic value of the hedging strategy compared to the expected value associated with a naïve approach. For example, Kanudia and Loulou [91] performed a GHG abatement analysis of Quebec and Ontario and calculated the EL for all four perfect foresight strategies, and concluded that the high EL demonstrates the significance of cost savings in following the hedging strategy. Hu and Hobbs [81] used VSS to quantify the cost of ignoring uncertainty in GHG policy, and advised energy companies to consider GHG limits when making decisions. Another closely related metric, the value of policy coordination (VPC), was also calculated to measure the difference between a naïve strategy that assumes no future policy change, and a strategy that expects future policy modifications announced by policy makers. VPC showed that avoiding unexpected policy changes and providing early information on CO_2 caps and pollution laws would result in significant cost savings.

3.2.3. Limitations

Stochastic programming is able to provide a single hedging strategy that is highly desirable by decision makers; however, this approach also suffers from similar issues as MCA in terms of calculation burden and the requirement of uncertainty-related information. The processing time for MCA increases almost linearly with the number of iterations, but does not increase with the number of uncertain parameters.

By contrast, stochastic programming suffers from the infamous "curse of dimensionality" [92], where the number of SOWs increase exponentially with the number of uncertain parameters and the number of stages. Since the implementation of stochastic programming is based on directly solving equivalent deterministic problems, only a small subset of uncertain parameters can be analyzed. For example, stochastic MARKAL limits the number of stages to two and number of scenarios to nine [85], and the stochastic version of the TIMES model is in practice limited to a small number of scenarios [83]. All studies we reviewed have 2 or 3 time stages and most of them have no more than 10 SOWs.

3.3. Robust optimization

3.3.1. Principle

An alternative approach called "Robust Optimization" can be used

Table 4
Stochastic programming literature.

Model	Research Question	Coverage and Time Horizon	Uncertain Inputs	Metrics	Stage & Scenarios	Key Insights
TIAM World [115]	Evaluate the impact of climate change on economic assessment of long-term energy policies	Global All sectors 2005–2030	Climate Sensitivity		2 Time Stages 4 Scenarios	Climate sensitivity is the main uncertainty. Availability of carbon-free technologies is important, but there is no silver bullet
MARKAL [116]	Analyze technological and policy-related uncertainties in the US electric sector	US Electric sector 2015–2050	Climate change policy CCS technological availability Nuclear availability	VSS VOC EVPI	2 Time Stages 3 Scenarios	Incorporating uncertainty into capacity planning significantly reduces risks from more stringent climate policy. Nuclear and wind deployment hedges against uncertainty in CCS availability
MARKAL [117]	Demonstrate the use of a specialized software SETSTOCH to solve stochastic programming problems in MARKAL	Fictitious model	CO2 Emissions		3Time Stages 3 Scenarios	The specialized solver requires minimal coding and is able to solve very large problems
MARKAL [118]	Explores the potential energy reduction in steel, aluminium and cement industries	India All Sectors 2001–2031	GDP Growth		2 Time Stages 3 Scenarios	
MARKAL [81]	Impact of uncertainties in electricity demand growth, natural gas prices and power sector greenhouse gas regulations on electric power sector investment	US All sectors (Power sector focused) Energy market 2000–2050	Natural gas costs CO2 cap Demand growth	ECIU EVPI VPC	2 Time Stages 3 Scenarios for each uncertainty, 6 scenarios for combined analysis of CO2 cap and demand growth uncertainties	Carbon cap uncertainty is economically more important compared to electric demand and natural gas uncertainties
Temoa [12]	Introduces the stochastic programming feature of the Temoa model	All sectors	Energy import prices		2 Time Stages 81 Scenarios	
MARKAL [91]	Describe the stochastic programming approach with illustration on greenhouse gas abatement. In Quebec	Ontario and Quebec All sectors 1995–2035	End-use Demand GHG emission limits	EL EVPI	2 Time Stages 4 Scenarios	The hedging strategy has significant lower expected system cost compared to PF strategies Significant cost saving when inter-regional cooperation is enabled
MARKAL [88]	GHG abatement in Quebec	Quebec All Sectors 2035	End-use Demand GHG emission limits	EVPI	3 Time Stages 4 Scenarios	Hedging decisions are different from deterministic scenarios, and do not lie on their intermediate level High EVPI shows the importance of information on uncertainties
MARKAL [119]	Impact of uncertainties in GDP growth and carbon tax in energy planning	India All Sectors 1995–2035	GDP Growth Carbon Tax		2 Time Stages 9 Scenarios	Increased energy supply capacity is required to anticipate high GDP growth. Increased proportion of natural gas and decreased proportion of coal to account for possible increase in carbon tax
TIAM [120]	Assessing the role of CCS in climate mitigation	Global All sectors 2005-2100	Climate Target CCS capacity		2 Time Stages 6 Scenarios	Early actions are required for deep CO2 emission reductions CCS is important in climate mitigation and is influenced heavily by the mitigation target
TIAM [90]	impacts of long-term technology and climate uncertainties on the optimal evolution of the World energy system	Global All sectors 2010-2100	Availability and characteristics of low-carbon technologies		2 Time Stages 2 Scenarios	Gas is a more robust hedging option compared to nuclear and CCS
TIAM [82]	Analyzed climate stabilization strategies in the long run	Global All Sectors 1998-2100	Climate Sensitivity GDP	EVPI	2 Time Stages 8 Scenarios	3 °C temperature increase by 2100 can be achieved at very moderate cost, 1.9 °C target requires very high cost. Early actions are required. Climate sensitivity uncertainty has great impact, GDP growth rates have very little impacts
MARKAL [80]	Use Minmax Regret strategy to explore uncertainty in carbon reduction targets.	Quebec (Canada) All sectors 1993–2037	Cumulative GHG Abatement		2 Time Stages 5 Scenarios	MMR is suitable when the number of outcomes of the uncertain event is large. MMR recommends early mitigation actions even without knowledge of true target
TIMES [121]	Analyze the effect of uncertainty in cumulative carbon cap to South Africa	South Africa All sectors 2015–2060	Cumulative carbon cap		2 Time Stages 2 Scenarios	Hedging strategy shows that investment in new generation capacity is required.
TIMES [122]	Effect of short-term wind power uncertainty in a long-term Danish heat and electricity system.	Denmark 2010–2050 heat and electricity sector	wind power availability electricity prices,	VSS	2 Time Stages 90 Scenarios	Compared to deterministic approach, the hedging strategy has lower system costs, investments in wind, expected electricity export, and higher expected biomass consumption.
TIAM [123]	Analyze the effect of climate sensitivity uncertainties	Global All sectors 2000-2100	Climate Sensitivity		2 Stages 4 Scenarios	Intermediate actions are required, and total emissions need to be reduced by about 40% by 2040

(continued on next page)

Table 4 (*continued*)

Model	Research Question	Coverage and Time Horizon	Uncertain Inputs	Metrics	Stage & Scenarios	Key Insights
MARKAL [124]	The effect of uncertainties in fossil fuel prices and biofuel availability on investment decisions	UK All Sectors 2000–2050	Fossil fuel prices Biofuel availability	EVPI	2 Time Stages 10 Scenarios	Hedging strategy is different from deterministic scenarios or an "average" of the deterministic scenarios. Fossil fuel price uncertainty is extremely expensive compared to biomass uncertainty Long-life technologies cause path dependencies and may perturb recourse strategies. A broad technology portfolio with short life-span technologies better hedges against uncertainties
MARKAL [51]	Provide near-term insight under uncertainties in emission reduction target required	UK All Sectors 2000–2050	Cumulative emissions by 2050 (80% and 90%)	EVPI	2 All Time Stages 2 Scenarios	Steep near-term decarbonization is important. The cost of uncertainty is relatively high when the scenario weightings are close, and reduces when moving away from equal weightings
MARKAL [51]	Provide near-term insight under uncertainties in emission reduction target required	UK All Sectors 2000–2050	Cumulative emissions by 2050 (80% and 90%)	EVPI	2 All Time Stages 2 Scenarios	Steep near-term decarbonization is important. The cost of uncertainty is relatively high when the scenario weightings are close, and reduces when moving away from equal weightings

to avoid the computational burden and consider a large set of uncertain parameters while remaining numerically tractable. The uncertain parameters have set-based definitions and require minimal uncertainty information. Only the range of variation is required for each parameter and no probability distribution is needed. The principle of robust optimization is "immunizing a solution against adverse realizations of uncertain parameters within a given uncertainty set." [93] The formulation of robust optimization may take a few different forms. Below is the formulation used by Labriet and et al. [93] based on Bertsimas' [94] approach:

Consider the linear problem,

$$\begin{cases} \min c^T x \\ s.\ t.\quad Ax \le b \\ x \in \mathbb{R}^+ \end{cases}$$

The constraint coefficients matrix A represent the exogenous model parameters such as energy prices and investment costs. It is assumed that only the coefficients $a_{i,j}$ $(i \in I,\ j \in J)$ in matrix A are affected by uncertainty. By setting $a_{i,j} = \overline{a_{i,j}} + z_{i,j}\widehat{a_{i,j}}\, z_{i,j},\ z_{i,j}\ \varepsilon\ [-1,\ 1]$, the nominal value $\overline{a_{i,j}}$ of the coefficient $a_{i,j}$is allowed to vary symmetrically by $\widehat{a_{i,j}}$. The linear problem incorporates these uncertain coefficients and reformulates into another linear problem called the equivalent robust counterpart as shown below.

$$\begin{cases} \min c^T x \\ s.\ t.\quad \sum_j \overline{a_{i,j}} x_j + \max_{z_{i,j}} \sum_j z_{i,j} \widehat{a_{i,j}} x_j \ \le b_i \\ z_{i,j}\ \varepsilon\ [-1,\ 1] \qquad \forall\ i \in I,\ j \in J \\ \sum_{i,j} |z_{i,j}| \ \le\ \Gamma \quad \forall\ i \in I,\ j \in J \\ x \in \mathbb{R}^+ \end{cases}$$

Γ is the budget of uncertainty that controls the total number of parameters that are allowed to vary. When $\Gamma = 0$ the constraints are equivalent to that of the nominal problem without uncertainties, and $\Gamma = |I| + |J|$ represents the worst case problem where all uncertain parameters take extreme values. By setting different Γ values the modeler is able to control the level of pessimism, where the most pessimistic case equals the worst-case scenario.

3.3.2. Applications

The robust optimization technique was first developed Soyster [95] and was subject to numerous subsequent development [94,96,97]. Babonneau et al. [98] first proposed the use of this method in environment and energy optimization models. We reviewed 3 studies that applied this technique to ESOMs. The main policy insights include the cost to hedge against uncertainties, key hedging technologies, and quantification of uncertainty source importance.

Lourne [99] used robust optimization to analyse the impact of energy technology cost uncertainty for the French transport sector in the MIRET model, which was developed as an instance of the TIMES model. The cost deviation was set to 15% and the cost budget Γ was varied from 0% to 50%. The results show that with increasing uncertainty budgets, the model choose technologies with less cost uncertainty, and therefore result in a more diversified technology mix and a rise in total system costs to hedge against uncertainties.

A related study Labriet et al. [93] analyzed the impacts of uncertainties in investment costs and primary energy costs, including fossil fuels and biomass on carbon mitigation under the same modeling framework. It was assumed that 120 uncertain parameters can rise by 10% and a sensitivity analysis was performed on the cost budget. The results showed that the total system cost increased by up to 11% compared to scenarios without uncertainty considerations. The cost increase can be interpreted as the cost of robustness to hedge against uncertainties in technology costs. Scenarios with higher uncertainties have a more diversified fuel usage, which proves that diversification is a good hedging strategy. Technologies like biofuel have higher penetration in scenarios with higher uncertainty budgets. These technologies can be considered robust hedging technologies against cost uncertainties. The shadow values of the robust counterpart measure the impacts of uncertain parameters on the optimum objective function, and quantify the relative importance of uncertain sources. The costs of primary energy were found to be the most critical uncertainty sources.

In a methodologically oriented paper, Babonneau et al. [100] demonstrated the approach in an energy security analysis of Europe with the TIAM-world model. The formulation specifies the desired level of diversification in energy supply, import dependency, and the reliability target representing the probability to guarantee energy security. A key policy insight is that with an extra 0.7% of total energy cost, near 100% reliability of EU energy supply could be guaranteed. The reliability improvement is achieved mainly through shifts from imports to indigenous resources; a relatively small contribution comes from expanding the capacity of energy import channels. In addition, four quantitative metrics were used to show that increasing reliability significantly reduces the concentration of supply sources. The contribution from expanding the capacities of energy import channel to reliability is relatively small.

3.3.3. Limitations

Robust optimization overcomes some of the shortcomings of MCA and stochastic programming approaches by offering a parsimonious way of calculating risk-averse solutions However, it loses some of the merits that the other two approaches could bring. Robust optimization can identify which strategies are more robust under uncertainties, but it fails to provide a unified hedging strategy like stochastic programming. It also contributes to the better understanding of which uncertainty sources have greater impacts on the model results; however, when probability distributions and covariance among inputs can be determined, the additional information related to uncertainty can be potentially better captured by MCA.

3.4. Modelling to generate alternatives

3.4.1. Principle

The uncertainty techniques we discussed in previous sections, including sensitivity analysis, MCA, stochastic programming and robust optimization, can only address parametric uncertainties. Analysts have repeatedly called for more focus on structural uncertainties in ESOMs [12,52,68], though efforts have been minimal. Modelling to generate alternatives (MGA) is a technique that can help address structural uncertainties.

Conventional ways to reduce structural uncertainty include using larger and more complex models to better represent real world dynamics, comparing different models [101], and subjecting model relationships to expert review [102]. DeCarolis [103] noted that increasing model complexity does not eliminate structural uncertainties. Since ESOMs attempt to model a highly complex reality under deep uncertainty, structural uncertainties and unmodeled objectives will always be present. As a result, model solutions lying within the feasible, near optimal region may be more desirable than the optimal solution when unmodelled considerations, such as unforeseen or unmodelled risks, are brought to bear on the scenario.

The principle of MGA is to relax the optimal solution, and use a modified model formulation to search the near-optimal solution space for alternative solutions that are maximally different in decision space. MGA can be broadly interpreted as any method used to systematically search the near optimal solution space for alternative solutions. The Hop-Skip-Jump (HSJ) method, proposed by Brill et al. [104], represents one such MGA approach:

Step 1. Solve the original problem to obtain an initial optimal solution.
Step 2. Obtain an alternative solution using the formulation:

$$minimize \sum_{k\varepsilon K} X_k$$

$$Subject\ to f_j(\vec{x}) \le T_j \quad \forall\, j$$

$$\vec{x} \in X$$

Where

K = set of indices of the decision variables that are nonzero in all previous solutions
X = set of feasible solutions based on the "technical" constraints of the model.$\vec{x} \in X$ implies that the constraints of the original problem hold for the alternative solution
$f_j(\vec{x})$ = j^{th} objective function in the original formulation
T_j = Target value for the j^{th} modeled objective

This new formulation is designed to search for highly different solutions in decision space by minimizing the weighted sum of the decision variables that appeared in previous solutions. Each target value T_j is calculated by adding a specified amount of slack to the objective function value obtained from Step 1. Applying the adjusted objective function as a constraint ensures that the alternative solution is within a prescribed inferior region near the original optimal solution.

Step 3. Iterate the reformulated optimization in Step 2 to generate a series of alternative solutions that are different from all previous ones. The new objective function minimizes the sum of all nonzero variables in all previous solutions.
Step 4. Terminate when no significant changes to decision variables are observed.

The MGA algorithm should be adapted to suit the analysis at hand, and should consider the form of the revised objective function, the updating procedure for objective function coefficients, and the chosen slack value. The MGA-based results should be screened for plausibility and interpreted carefully in light of the study objectives.

The alternative solutions produced by MGA reveal possible future options that may be otherwise overlooked. As decision makers may be concerned with factors outside of the modelling scope, such as political tractability or equity, the alternative strategies may be preferable and more policy relevant than the optimal solution in the base case. In addition, as the alternative solutions are generated by a computer algorithm, MGA alleviates the cognitive bias issues associated with scenario analysis, whereby detailed storylines underlying different scenarios can appear cognitively compelling despite the underlying uncertainty [53]. Finally, MGA can help unmask “knife edge” solutions in the base case, where slight perturbations to input assumptions can produce very different solutions.

3.4.2. Applications

MGA is an emerging and innovative method for ESOMs and we have reviewed four related studies. DeCarolis [103] first introduced this method for energy models, then later applied it to the TEMOA model [105] to explore alternative energy futures in the US electric and light duty transport sectors. Four sets of MGA runs with slack values representing 1%, 2%, 5% and 10% energy supply cost were performed, and the total energy output of technologies over the model horizon were chosen as decision variables in the MGA runs. Compared to the base case scenarios and carbon-constrained scenarios, the MGA scenario results demonstrate a more diverse set of deployed technologies, and the variety increases with the slack level. Technologies such as IGCC, biomass, and wind have significantly higher penetration in MGA scenarios, indicating that they could play a significant role in achieving a low carbon future. Trutnevyte [106] employed the EXPANSE (Exploration of Patterns in Near-optimal energy ScEnarios) model to evaluate the economic potential of renewable energy sources for heat

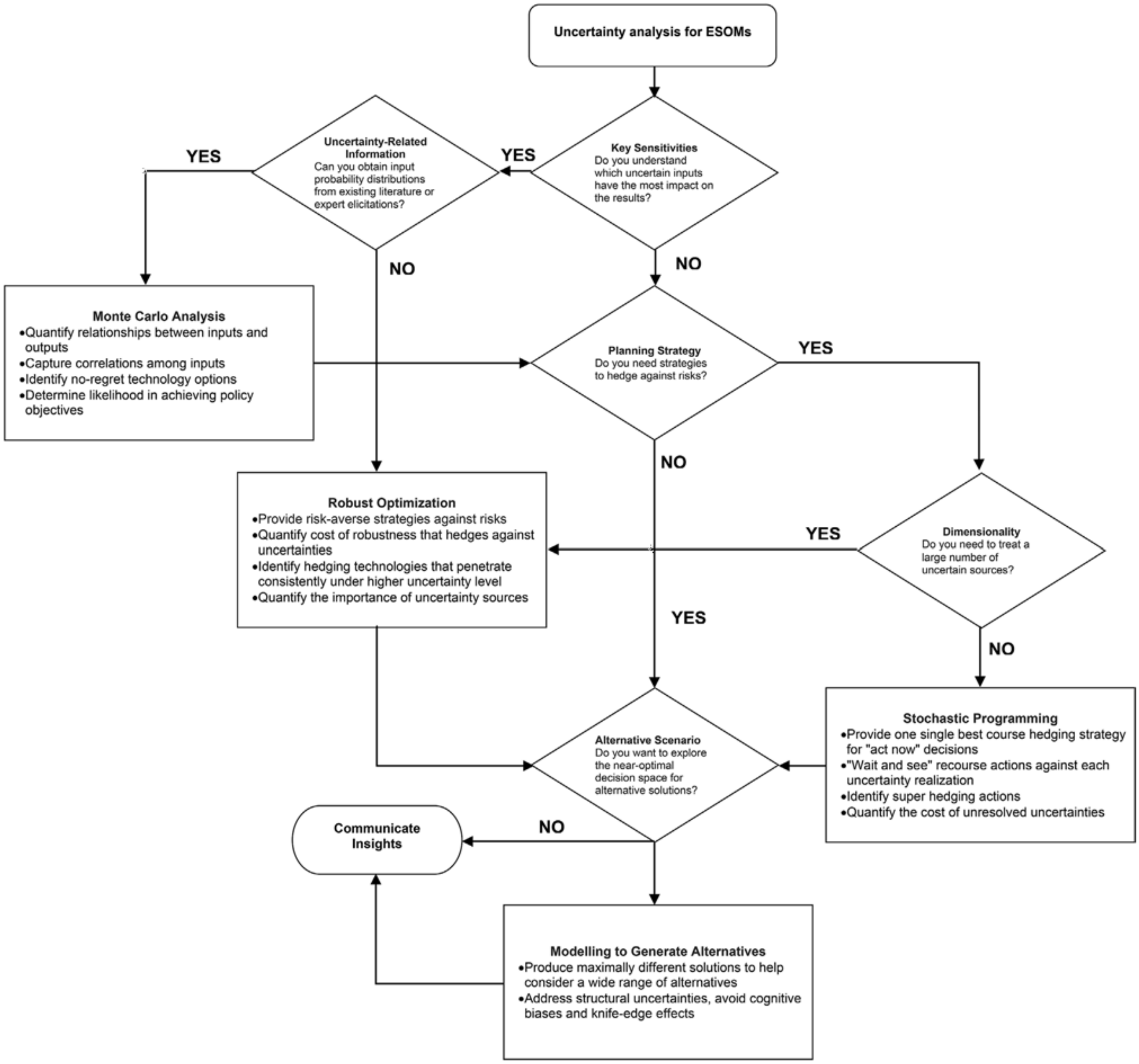

Fig. 4. Uncertainty technique selection flowchart.

supply, and demonstrated the interactions among different energy sources. The EXPANSE model was also used to explore 800 different pathways for the UK power sector using a combined approach of MGA and Monte Carlo sampling [107]. The analysis considers a large number of uncertainties and produces ranges of generation capacity and investment cost in 2050. The multiplicity of near-optimal solutions with different power generation mixes supports the current UK policy of maintaining a liberalized and technology neutral electricity market. Price and Keppo [108] implemented a revised MGA algorithm into the TIAM-UCL model that produced solutions that are maximally different in terms of cumulative primary energy consumption by fuel type.

3.4.3. Limitations

The MGA results depend on the slack value, which is subjectively chosen. The alternative scenarios represent plausible future alternatives, but associated probabilities are not attached to the scenarios. Therefore, the findings produced from this approach do not yield a unified, near-term decision making strategy that accounts for future uncertainty. In addition, even though the alternative scenarios can be valuable in outlining future possibilities, they may also be used to justify pre-existing policy preferences. Finally, MGA allows modelers to consider structural uncertainties in a limited way. Other approaches to address structural uncertainty should be considered, particularly ones that integrate insights from models with fundamentally different structures.

4. Discussion and conclusion

The value of energy system modelling is on highlighting policy implications rather than providing absolute numbers - providing insights rather than answers. Compared to conventional scenario analysis, assessing uncertainties in a systematic manner helps improve the robustness of results and provide additional insights associated with multiple outcomes. In this paper, we carried out a comprehensive review of uncertainty techniques that have been applied to ESOM models: Monte Carlo analysis, stochastic programming, robust optimization, and modelling to generate alternatives.

A key finding arising from this review is that each of the four uncertainty analysis techniques has its own focus, advantages and limitations, and informs different aspects of decision-making. Choosing a specific uncertainty technique should involve consideration of issues such as data availability, the uncertainty space to be covered, and the type of policy questions to be answered. Fig. 4 provides guidance and recommendations for modellers in the form of a flow chart that summarizes the key policy insights for each technique and a basis for selecting which uncertainty technique to use. It is also worth noting that uncertainty analysis approaches are not mutually exclusive and should be used in a complementary manner to provide well-rounded analysis.

MCA can be applied when information on probability distributions could be obtained through existing studies or expert elicitation. In addition to quantifying the feasibility in reaching policy targets and identifying robust technologies, MCA can also be run in tandem with GSA to map the relationships between inputs and outputs, which improves model transparency and unpacks model structure. As the only approach for sequential decision-making, stochastic programming is best used when the number of uncertain sources under concern is small. It can be used to provide a single optimal hedging strategy that can help guide near-term action. Such an approach avoids the issue with multi-scenario approaches, where the scenario ensemble may leave the decision makers in a quandary. Robust optimization is a computationally efficient approach for handling uncertainties associated with a large set of parameters while requiring minimal information on the distribution of uncertain parameters. It computes the cost of hedging against risk at a prescribed level of uncertainty, and indicates which technologies are critical in reaching the desired policy targets. MGA is currently the only systematic approach that addresses structural uncertainties, and can be combined with other approaches.

Even though it is widely accepted that uncertainty is a key issue for energy models, the results of our literature review indicate that the number of studies that actually apply formal techniques to address uncertainties for ESOMs models is limited. For example, info-gap decision theory (IGDT) [109–111] is a well-established uncertainty analysis method for the power system; however, none of the ESOM studies have applied IGDT, and only three studies used the alternative approach of robust optimization. One possible cause is the difficulty and additional efforts required in modifying model formulations and developing stochastic model infrastructure. The popularity of uncertainty analysis was found to be strongly related to the stochastic features that the model provides. Most of the stochastic programming analysis studies have been carried out with the MARKAL/TIMES model generators using the built-in stochastic programming feature, but only a few MCA studies have been carried out with these models. The application of MCA with the TIMES family of models may gain popularity if computational features similar to that in ESME or PROMETHEUS models is provided for queueing, processing and storing the model runs. Emerging techniques such as robust optimization and MGA also require considerable modifications in the mathematical formulation, which raises difficulties for modelers who want to apply these methods in their analysis. Deploying systematic uncertainty approaches for additional policy insights is important and therefore we recommend incorporating features that enable stochastic programming analysis into new or existing models, since these may encourage model users to go beyond simple scenarios.

Besides developing stochastic features for existing models, future research on uncertainty modelling should consider a broader range of uncertainties, explore new techniques to treat these uncertainties, address uncertainty of pertinent climate change issues, such as exploration of uncertainty around keystone technologies, and reflect on uncertainties associated with policy, politics and societal factors [112]. Currently, the majority of ESOM studies rely on historical data or expert judgements to address uncertainties for existing technologies such as electric vehicles and bioenergy. The well below 2° target set by the Paris agreement necessitates the analysis of more ambitious national and global climate targets. ESOM models should therefore further consider feasibility and uncertainties of emerging technologies such as direct air capture, as well as more speculative technologies made cost-effective through potential technology breakthroughs. In addition, policy uncertainties are increasingly relevant after the US withdrawal from the Paris Agreement [113]. Rather than assuming a perfect foresight over the next several decades, modellers should be aware that decisions can be made myopically [114], and constantly seek better ways to properly assess and communicate uncertainties in policy changes.

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