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Improving robustness in strategic energy planning: A novel decision support method to deal with epistemic uncertainties

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Abstract

This paper addresses the challenge of dealing with epistemic, i.e. non-probabilistic, uncertainties in strategic energy planning modelling. Current models have limited consideration of this type of uncertainty compared to probabilistic uncertainty, and also typically lead to overly conservative results. To address this issue, the contribution of the paper is to propose a novel decision support method which combines two decision-making methodologies into a single, internally consistent algorithm, and to show its applicability to real-size energy planning studies. Robust optimization is applied to address constraint uncertainties, while the minimax regret criterion is utilized for uncertainties in the objective function. This approach facilitates energy modelling exercises that can be more closely aligned with decision-makers' preferences for both feasibility and optimality. To demonstrate its effectiveness, the method is applied to a real-size strategic energy planning model, and the algorithm is shown to be able to provide detailed solutions in reasonable times. Ex-post evaluations confirm that this approach maintains robust optimization performance by effectively reducing the occurrence and magnitude of infeasibilities, while satisfying the minimax regret criterion across the entire range of uncertainties. Therefore, this integration preserves the distinct advantages of each methodology without any adverse effects when used together.

Keywords: Strategic energy planning; Decision support; Uncertainty; Robustness; Robust optimization; Regret.

1. Introduction

Energy planning consists of deciding the type of energy investments required to provide the energy services society demands; when these investments are needed; and the policies that may be required for them to take place. It can be done by central planners, the market itself, or a mixture of both, generally with the aid of mathematical models [1]. This exercise is particularly relevant for decision-making aligned with the attainment of the 7th Sustainable Development Goal or net-zero targets, among others.

Energy planning models require input parameters typically related to the techno-economic characterization of energy sources, technologies and service demands, among others. However, the long life of energy technologies, which usually last between 20 and 50 years, means that energy models should consider a similar time frame, giving rise to many uncertainties in such a long period including climate change, technological advances, geopolitical stability, social changes, and extreme events. These uncertainties, which are beyond the control of decision-makers, can be classified as external parametric uncertainties. Moreover, most of these parametric uncertainties can also be considered epistemic, meaning there is not enough information or knowledge about them, so their behaviour cannot be reasonably predicted, and probabilistic functions cannot be used.

Dealing with epistemic or non-probabilistic uncertainties is crucial in any decision-making process related to strategic energy planning, as failure to do so can result in detrimental consequences, such as unnecessary or obsolete energy investments, or a potential compromise of energy supply security, among other undesirable outcomes. An appropriate handling of uncertainties involves the use of suitable methodological approaches in the model. In addition, it is essential to take into account decision-makers' preferences concerning epistemic uncertainties, as these preferences can inform the selection of appropriate decision criteria.

An extensive literature review (see Table 1 in the next section, or Section 1 in the Supplementary Material) has shown that, although there is a significant amount of literature dealing with probabilistic uncertainties in energy models, in particular stochastic approaches (e.g. [2] or [3]), these methods are not able to deal with epistemic, non-probabilistic uncertainties. These uncertainties have been addressed in the literature mostly with Robust Optimization (RO) [4], [5], which looks for solutions that are feasible under all the range of uncertainties considered. However, although RO may be useful (albeit very conservative) in ensuring for example security of supply, its application to the objective function (i.e., uncertainty in costs) is more questionable: decision-makers are not generally completely risk-averse, and prefer to minimize maximum regret. This is indeed the decision-making criterion generally applied in scenario analysis [6], which in turn has a major drawback, in that it assumes that the preferred decision will be within the set of optimal solutions for each discrete scenario.

Therefore, a significant gap has been identified in that no energy planning models or published exercises exist that are able to apply, in an internally consistent way, these two different decision-making methods to ensure both feasibility in the constraints and optimality of the objective function, under non-probabilistic uncertainty, and for the whole range of feasible solutions.

The novel contribution of this paper is precisely to provide a single algorithm in which these two methodologies or decision-making approaches are used jointly in an internally consistent way. Robust Optimization is applied to ensure feasibility in the constraints, while minimax regret is the criterion employed for achieving acceptability of the objective function. The algorithm also searches for the minimax regret solution in all the feasible space, instead of only among discrete scenarios.

The application of the algorithm to a real-sized energy planning exercise shows that first, it can deliver detailed results within reasonable computing times; and second, that the solution found maintains robust optimization performance while minimizing maximum regret in the objective function. Therefore, the algorithm preserves the advantages of each approach without adverse effects or significant impacts on computing time.

The rest of the paper is structured as follows. As a preamble, Section 2 discusses a theoretical framework about the treatment of uncertainty in energy models and the concept of robustness, and reviews the main literature on these topics. Section 3 introduces the novel robust decision support method. Section 4 offers the results of applying and validating the novel methodology to a real-size strategic energy planning model. Section 5 presents conclusions and future work.

2. Dealing with uncertainty in energy models

Uncertainty can be defined as the distance between the available knowledge and the knowledge required for optimal decision-making [6]. It can be classified into two types: epistemic (Knightian) uncertainty, in which there is no knowledge about the potential value of the uncertain parameters, and probabilistic (aleatory) uncertainty, which can be modelled using probabilities due to some knowledge about the probability function that represents the parameter [7].

In such complex conditions where the lack of knowledge is notorious, as in the case of epistemic uncertainty in strategic energy planning, a decision process aims to adopt a rational choice, but this rationality is different for each decision-maker. A decision criterion should therefore be chosen in accordance with the subjectivity of the decision-maker, i.e. the attitude to face different realizations of the environment, which is exogenous and uncontrollable. This attitude is typically subject to risk aversion, i.e. decision-makers typically prefer, to a certain degree, to guarantee an adequate performance of an implemented policy or investment rather than risking a potentially better performance that could end up being a wrong decision.

Consequently, decision-makers' preferences in environments affected by epistemic uncertainties are generally identified in the literature as robust decision-making. Nevertheless, if the aim is to find robustness, this leads to some conceptual questions: How to define robustness? When can a decision be said to be robust? What does the optimum mean in the presence of epistemic uncertainties?

There is no single definition of robustness. Under one approach, it refers to the best performance decision in the worst possible environment [8]. Another way of understanding it is as the least sensitive decision to changes in the environment [9]. Therefore, the former aims to find the optimal value of the objective function for a single scenario (the worst realization of uncertain parameters), while the latter obtains the solution that varies the least when uncertain parameters change, so the objective function does not need to be optimal under any scenario. A third interpretation would be the minimization of regret [10]: it looks for the least opportunity cost decision for any environment realization.

These interpretations of a robust decision are often confused in the literature, while significant differences exist between them. Consequently, the methodologies used to address robustness may differ based on the specific understanding of this concept. One of the main reasons for the confusion surrounding robustness is the inconsistent use of the same term to describe different meanings. To help mitigate this issue, the proposed solution involves assigning distinct names to the different interpretations of robustness, allowing for greater clarity and differentiation between them:

- **Wald robustness** is achieved when the decision corresponds to the best performance solution in the worst-case scenario. It is related to the Wald (pessimistic) decision-making criterion.

- **Sensitivity robustness** is achieved when the decision corresponds to the least-sensitive solution to changes in the environment.
- **Savage robustness** is achieved when the decision corresponds to the minimum-regret solution to changes in the environment. It is related to the Savage decision-making criterion.

It is also essential to notice that epistemic uncertainties lead to a state of ambiguity that challenges the notion of optimality. If robust decisions are pursued, they do not necessarily have to be aligned with the classic concept of optimum, under which an objective function is maximized (or minimized) in the expected scenario or under stochasticity. It may be more appropriate to speak of suboptimal decisions that do not perform as well in the expected scenario, but guarantee adequate performances in the range of possibilities in which uncertainties can be revealed. In conclusion, both Sensitive and Savage criteria are not about making the best (optimal) decision for a particular scenario but about making a decision that performs reasonably well (suboptimal) within the uncertainty ranges.

2.1. Methodologies for dealing with uncertainties

In addressing uncertainty, methodologies can be classified into probabilistic and non-probabilistic, according to both types of uncertainty. Probabilistic methodologies deal with random uncertain parameters that can be approximated using historical data and expert knowledge through probability distributions. These methods are based on probabilistic criteria, such as the expected value [11], although others could also be used (median, mode, VaR, etc.). Although relatively easy to implement, they are computationally intensive, limited to a few uncertain parameters, and dependent on large amounts of historical data. The most commonly used probabilistic methods are stochastic programming and Monte Carlo simulation.

On the other hand, non-probabilistic methodologies are more suitable when addressing epistemic uncertainties, for which no probability functions are known. However, some limitations should be mentioned, such as obtaining too-conservative outputs. It is noteworthy that both probabilistic and non-probabilistic methods could be compatible in the same analysis [12]. More detailed information about these methodologies' inputs, advantages, disadvantages and applications can be found in Table 1.

Historically, the most widespread methodology in energy planning is **scenario analysis**, which is a suitable method for backcasting in sectors that may be affected by unprecedented events. For this reason, it is considered particularly appropriate for energy modelling. Each scenario is defined as a possible realization of uncertain parameters, resulting in a tree of scenarios which occurrence seems possible but not assured, from which possible solutions are extracted. The results facilitate understanding the system behaviour and dynamics [13]. Indeed, one of the crucial issues to be addressed when considering scenario analysis is defining which uncertainties are included in the model, since a compromise must be found between exhaustivity and the risk of omission of relevant uncertainties. It is essential to include as few factors as possible, so as not to turn scenario analysis into a difficult-to-use speculation-based tool, trying to identify a few decisive factors that are not easily predictable [14]. However, the interpretation of the results of different scenarios is always complex.

Recent developments in the scientific community have seen an increase in the adoption of alternative methodologies, such as **robust optimization**, due to the significant limitations of scenario analysis. It was first proposed by Soyster [15], but its application in different fields is relatively recent. This non-probabilistic methodology aims to solve the worst-case realization of uncertain parameters to ensure feasibility [16], therefore implicitly applying the Wald pessimistic criterion. This methodology generally looks for a solution where all constraints are satisfied for any realization of uncertain parameters within their uncertainty range, so feasibility is guaranteed. However, results may be too conservative. To prevent this, Bertsimas and Sim [17] (B&S) proposed a technique that maintains the linearity of the robust counterpart by using polyhedral uncertainty sets, and allows controlling the degree of conservatism by introducing a control parameter (τ) in the polyhedral uncertainty set. This parameter guarantees the feasibility of the solution if less than τ uncertain coefficients change. Moreover, there is a probabilistic guarantee: if more than τ uncertain coefficients change, the robust solution will be feasible with high probability.

It is crucial to consider the trade-off between robustness and performance: it is possible to include a large number of uncertain parameters, so the greater this number, the more robust. But it also means a more pessimistic decision, hence a lower performance of the objective function under the average scenario. Resolving this dilemma is one of the most critical issues when implementing this methodology.

Table 1 Methodologies for treatment of uncertainty

	Method	Input	Advantages	Disadvantages	Applications
Probabilistic	**Stochastic programming**	PDF	Easy implementation	Computationally expensive. Large amount of historical data. Able to consider a few uncertainties.	[2], [3], [18]–[20]
	Monte Carlo	PDF	Easy implementation	Computationally expensive. Large amount of historical data. Able to consider a few uncertainties. Slow convergence.	[21]–[23]
	Point-estimate	PDF	Very easy implementation	Simplistic method. Large amount of historical data.	[24]
	Possibilistic	MF	Converting linguistic knowledge to numerical values	Complex implementation. Historical data and expertise. Ambiguous results.	[25]–[27]
	Hybrid	PDF & MF	Dealing with both possibilistic and probabilistic uncertainty types simultaneously	Computationally expensive. Complex implementation. Large amount of historical data.	[28], [29]
Non- Probabilistic	**Interval Analysis**	Intervals	Useful when just an interval is available	The correlations among intervals are neglected. Conservative.	[30], [31]
	Scenarios Analysis	Scenarios set	Useful when no PDFs or MF available. Backcasting: Allows designing paths based on relevant scenarios.	Based on assumptions about uncertainties. Works as several deterministic scenarios. Limited to consider a few uncertainties.	[32]–[35]
	IGDT	Forecasted values	Robustness. Accurate for severe uncertainties. Useful when no PDFs or MF available.	Do not find the optimal, but most robust solution. Extremely conservative.	[9]
	Robust Optimization	Uncertainty sets	Robustness. Accurate for severe uncertainties. Useful when no PDFs or MF available.	Conservative.	[4], [36]–[39]

It is noteworthy to mention that alternative approaches for addressing uncertainties in decision models could also involve the utilization of machine learning techniques, such as Bayesian networks. These methods could be particularly useful for modelling systems where the relationships between parameters and variables are not predetermined, which is often the case in many energy systems. Machine learning techniques can also be used in conjunction with other methods to provide complementary insights. Relevant examples can be found in existing works from other fields, including [40].

Moreover, the consideration of deterministic chaotic variation, involving the introduction of a small perturbation at the initiation of a prognostic simulation that amplifies due to the use of discrete mathematical representations of continuous equations, is indeed noteworthy. To the best of current knowledge, this aspect has not been thoroughly addressed in the existing literature on energy models. Dynamic energy models may exhibit susceptibility to chaotic variation, wherein minor alterations in parameters, such as demand projections, can lead to substantial changes by the conclusion of the modeling period. It is important to recognize that this phenomenon is supplementary and spans both epistemic and probabilistic uncertainty, as it represents a characteristic inherent to uncertainty in dynamic models, rather than being specific to its epistemic or non-epistemic nature.

2.2. Applications to energy models

Several authors have previously addressed uncertainties in strategic energy planning models using probabilistic methods. On the one hand, the MARKAL/TIMES family of models developed by ETSAP (IEA) is widely used in energy system analysis, with variations for different purposes [41]. These models usually incorporate uncertainty through stochastic programming, with examples such as those developed for Quebec [2], the United Kingdom [3], and Belgium [42]. Some models, such as TIAM, have also incorporated stochastic approaches to deal with uncertain parameters [20]. However, models become intractable when they incorporate too many uncertainties, which has led to alternative proposals such as the TEMOA model [43], which uses a Modeling to Generate Alternatives (MGA) approach in order to explore near-optimal solutions [44]. Other approaches, such as Monte Carlo simulation, have also been used in several models. Some examples can be found in MESSAGE [45], ESME [46] and OSeMOSYS [47]. Another option is that proposed by trial-and-error models, which has been applied in various case studies, such as the analysis of Jacobson et al. [48], which explores the interdependencies among global warming, air pollution, and energy insecurity. Finally, it is important to highlight the coupling of energy models with climate models, as exemplified in [49]. This integration allows for a more sophisticated incorporation of relationships in the analysis of the climate-energy-economy interaction. The development of these coupled models is pivotal for comprehending the intricacies of multisectoral relations. In this context, while defining these relationships may help mitigate some uncertainties, the increased complexity introduced by such models can also introduce or exacerbate other uncertainties. Section 1 of the Supplementary Material contains a comprehensive table summarising the literature review on the treatment of uncertainty in the main energy planning models.

However, as mentioned before, probabilistic approaches are inadequate to deal with epistemic uncertainties. In this regard, robust optimization is an alternative that has been used in some applications for energy models. To review the literature, the study draws upon the research conducted by Moret et al. [4], expanding upon their analysis by exploring more features, such as the dynamic approach and decision-making criteria, and incorporating relevant new studies that have been published since their publication. A comprehensive literature review can be found in section 2 of Supplementary Material, its key findings being as follows: (i) robust optimization continues to be scarcely used within strategic energy planning models, although its use is growing; (ii) the methodology proposed by Bertsimas and Sim [17] is the most widespread, likely because it provides a significant plus for manageability and computational tractability; (iii) the most frequently considered uncertainties include energy demand, costs and prices; (iv) usually, only a few uncertainties are included, likely because most models were initially designed to work deterministically, and the inclusion of uncertainties is a significant challenge in reformulating the problem; (v) applications do not usually include wide-ranging models such as those for energy planning, but are limited to specific sectors, the most prominent being the electricity sector; (vi) the majority of the reviewed works have utilized the pessimistic Wald criterion, whereas a relatively small number have incorporated the Savage criterion; and (vii), several models are multi-stage, but when referring to strategic energy planning, they are static.

2.3. Current status and challenges of robust strategic energy planning

The studies conducted by Moret et al. [4] and Patankar et al. [5] have contributed significantly to the advancement of strategic energy planning models, introducing innovative robust approaches to address uncertainties in a practical manner.

Moret et al. [4] introduced a groundbreaking approach based on the B&S robust optimization technique, which was applied to both the objective function and constraints by employing a decision method called "*First feasibility, then optimality*". In a similar vein, Patankar et al. [5] also used the B&S robust optimization technique to include uncertainties in fuel prices and technology costs, which directly impact the minimization-cost objective function. Furthermore, Patankar et al. [5] addressed the challenge of uncertainties' autocorrelation, which poses a major obstacle in developing strategic energy planning models that align with real-world dynamics.

However, there is still room to enhance the methodological approach to effectively address uncertainties and achieve robust decisions that align with the preferences of decision-makers.

Concurring with Moret at al. [4], ensuring feasibility through Wald robustness is essential in uncertain environments, as decisions should consistently avoid constraint violations even under worst-case scenarios. Thus, the use of the B&S technique is fully justified and brings some significant advantages, as highlighted by Moret at al. [4]: *"by increasing the protection level, constraint violations are sharply reduced, both in terms of frequency, and in terms of mean and standard deviation. […] constraint violations start to become negligible at low values of the protection parameter. Thus, to obtain good protection levels it is not needed to be fully robust, which further confirms the interest of the approach by Bertsimas and Sim"*.

However, when it comes to optimality, it is not as critical as feasibility and does not require a similarly conservative approach. Therefore, applying robust optimization to uncertainties affecting the objective function may not be the most suitable option. The choice of methodology should be based on the type of robustness that better fits the decision-maker preferences. This implies exploring different robustness approaches for both constraints and objective function uncertainties.

This divergence between decision-makers' preferences for feasibility and optimality becomes apparent in both works. Moret et al. [4] find that "*solutions obtained at medium uncertainty budgets […] offer more stability and protection against unfavorable realizations of uncertainty*". It means that lower standard deviation solutions are preferred at the expense of higher costs in the average scenario. Similarly, Patankar et al. [5] reveal that "*a robust strategy that explicitly considers future uncertainty has expected savings in total system cost of 12% and an 8% reduction in the standard deviation of expected costs relative to a strategy that ignores uncertainty*". In summary, the stability of decision outcomes becomes a crucial criterion.

Therefore, these methodological approaches do not adequately align with the desired decision criterion. Despite their goal of enhancing stability by achieving a low-sensitiveness decision, these approaches rely on robust optimization techniques to handle uncertainties within the objective function. This reliance on robust optimization implies a dependence on Wald robustness, whereas their true aim is to pursue Sensitive robustness. Additionally, the application of an ex-post probabilistic analysis to determine the protection level presents a significant challenge: if the aim is to make a decision that considers epistemic uncertainties and avoids reliance on probability functions, it is not consistent to employ them in the final decision-making process.

Consequently, uncertainties affecting optimality may be treated with alternative Sensitivity or Savage robustness-oriented techniques. The IGDT methodology, which maximizes the allowed deviation of uncertainties while ensuring a reference value for the objective function, could be suitable for Sensitivity robustness [9]. However, IGDT can be seen as the dual methodology of robust optimization, maximizing the uncertainty ranges for the worst possible cost (i.e., the reference value) instead of minimizing the cost for the worst possible realization of uncertainties within their range. Moreover, setting this reference value may be conflicting, considering the existing trade-off between the minimum value of the objective function to be guaranteed and the width of the range allowed for the uncertainties. This trade-off is similar to the one affecting robust optimization. Furthermore, implementing this technique to address uncertainties in the objective function inevitably leads to non-linearities due to the multiplication of uncertain parameters with decision variables.

An alternative approach for handling uncertainties is Savage robustness, which aims to minimize the maximum (minimax) possible regret, i.e., the greatest possible deviation between the chosen decision and the optimal decision when uncertainties become known. Regret has been widely used to address cost-related uncertainties and is closely aligned with decision-makers' preferences for optimality.

However, regret has been conventionally determined through scenario analysis [10]. This approach involves deriving optimal decisions based on a limited number of discrete scenarios. Subsequently, the payoff matrix associated with each decision in each scenario is evaluated, thereby allowing for the computation of a regret matrix. However, this approach restricts the set of potential decisions by solely considering the optimal solutions in each discrete scenario. This imposes unnecessary limitations since the minimax regret approach may result in suboptimal outcomes across all those scenarios. Therefore, a procedure to find the minimax regret solution from a continuous set of alternatives is needed, such as a minimax regret algorithm for linear programs with interval objective function coefficients [50].

However, this technique has been up to now applied in isolation, without considering alternative methods for addressing epistemic uncertainties in the constraints. To address this gap, a joint application of two distinct methods is required to handle uncertainties in both the objective function and constraints. This integration ensures that the decision-maker's preferences are adequately captured during the decision-making process in the face of uncertainties affecting both the objective function and the constraints.

3. A novel decision support method based on decision-maker's preferences

This proposal integrates two techniques into a single decision-making method: robust optimization utilizing the B&S technique to address uncertainties in the constraints, and a minimax regret algorithm for linear programs with interval coefficients to handle uncertainties in the objective function.

The novelty of the contribution lies in the fact that the proposed methodology, to the best of current knowledge, is the first to combine these two distinct methodologies in an effort to align decision-makers' preferences with different notions of robustness. The objective is to incorporate Wald robustness to ensure feasibility even in the most adverse scenarios, while simultaneously incorporating Savage robustness to minimize the feeling of economic loss in the face of any environment realization. This enables the implementation of practical energy modelling exercises that effectively reflect real-world decision-makers' preferences. Additional demonstrations regarding the applicability and performance of this novel decision-making method have been presented in Section 4, employing both a real-size energy model and a simplified version to verify and interpret the results.

3.1. Robust optimization in the constraints

As previously argued, the B&S [17] technique appears to be suitable for uncertainties in the constraints. It is based on the Wald robustness criterion and is known to reduce conservatism. Specifically, this technique uses a control parameter τ to indicate the number of uncertain parameters that take their worst value. Along with this control parameter τ, two additional variables are included, W and P, which are used to build the robust counterpart. The degree of protection is increased by adding one unit to the value of the control parameter τ, from 0 (all uncertain parameters at their nominal value) to Γ (all uncertain parameters at their worst value).

To ensure a clear understanding of the application of the B&S technique, an example is presented that considers the exogenous energy demand parameter $D(s,t)$ as uncertain, which is usually considered one of the most critical uncertainties regarding feasibility. This instance pertains to the implementation of the case study and a thorough exposition of its formulation is available in Section 4 of the Supplementary Material.

$$\sum_{g \in GEN} \boldsymbol{x_{op}}(g,t) + \boldsymbol{x_{ens}}(t) \geq \sum_{s \in DS} D(s,t) \;\; \forall t \in TS \quad (1)$$

Equation (1) would correspond to the energy demand balance at each time slice: the sum of final energy required by demand sectors $D(s,t)$ should be satisfied by the sum of energy supplied by each generation technology $\boldsymbol{x_{op}}(g,t)$, and the sum of the energy not supplied slack variable $\boldsymbol{x_{ens}}(t)$.

$$\sum_{g \in CE} \boldsymbol{x_{op}}(g,t) + \boldsymbol{x_{ens}}(t) - \sum_{s \in DS} D(s,t) - W(t)\,\tau \; - \; \sum_{s \in DS} P(s,t) \geq 0 \;\; \forall t \in TS \quad (2)$$

$$W(t) + \; P(s,t) \geq \delta_D(s,t) \;\; \forall s \in DS, \forall t \in TS \quad (3)$$

The energy demand balance constraint (1) is transformed into its robust counterpart in (2) and (3), where τ is the protection parameter, W and P are additional variables to build the robust counterpart, and δ_D is the maximum worst-case deviation of the energy demand from its nominal value, according to its uncertainty range.

Applying the B&S technique to other uncertain parameters is direct through a similar formulation of other constraints and would not mean a considerable increase in the computational burden.

3.2. Minimax regret in the objective function

Inuiguchi and Sakawa [50] proposed an iterative method by which it is possible to obtain the minimax regret for linear programs with interval objective function coefficients. In this way, they were able to ensure that, for the entire range of values within the defined uncertainty set, the decision obtained would be the best according to the minimax regret criterion. Subsequently, Mausser and Laguna [51] proposed a new algorithm that solves this problem more efficiently, using fewer integer variables and reducing the computational burden. For this reason, this is the algorithm introduced into the novel decision support method.

The minimax regret algorithm proposed in [51] is based on a linear maximization problem, in which uncertain costs are defined as interval coefficients $\mathbf{c} \in \mathbf{\Gamma} = \{\mathbf{c} \in R^n \mid \underline{c_i} \leq c_i \leq \bar{c}_i \text{ for } 1 \leq i \leq n\}$, where $\underline{c_i}$ and $\bar{c}_i$ are the lower and upper bounds, respectively, also known as *extremals*. The uncertainty set for uncertain costs can be defined as $\mathbf{\Psi} = \{i \mid \underline{c_i} < \bar{c}_i\}$. The goal is to find an $\boldsymbol{x} \in \Omega$ that minimizes the maximum regret for the whole uncertain cost interval.

The x-*optimality* property implies that the maximum regret associated with any cost parameter $\boldsymbol{c}$ is $R(c,x) = \max_{y\in\Omega}(c^T\boldsymbol{y} - \boldsymbol{c}^T\boldsymbol{x}) = (\max_{y\in\Omega} c^T\boldsymbol{y}) - \boldsymbol{c}^T\boldsymbol{x}$. It immediately follows to $y = x_c$, where x_c is the optimal solution.

If $R_{max}(x) = \max_{\boldsymbol{c}\in\Gamma}\{R(c,x)\}$ is the maximum regret for x considering any possible uncertain cost c, the objective is to find x^* satisfying $R_{max}(x^*) \leq R_{max}(x)$ for all $\boldsymbol{x} \in \Omega$. Therefore, x^* is the optimal solution to the Minimax Regret problem (MMR) [51].

MMR can be solved by an iterative relaxation procedure, in which $\boldsymbol{\Gamma}$ is replaced by a finite set of scenarios $C = \{\boldsymbol{c}^1, \boldsymbol{c}^2, \dots, \boldsymbol{c}^m\}$. This relaxation allows obtaining a linear formulation for MMR:

$$\begin{aligned} &min \quad && r \\ &\text{s.t.} \\ & && c^k\boldsymbol{x} + r \geq c^k\boldsymbol{x}_{c^k} \quad \forall c^k \in C \\ & && \boldsymbol{x} \in \Omega \\ & && r \geq 0 \end{aligned} \tag{4}$$

where each constraint $c^k\boldsymbol{x} + r \geq c^k\boldsymbol{x}_{c^k}$ is known as *regret cut*. Being $\widehat{\boldsymbol{x}}$ the solution to MMR, with corresponding regret $\widehat{\boldsymbol{r}}$, it is worth noting that $\widehat{\boldsymbol{r}} \leq R_{max}(x^*)$ is a non-decreasing lower bound if more regret cuts are added.

The set of cost scenarios C needs to be built, which can be done iteratively. The idea consists of finding the cost scenario that maximizes regret for a candidate solution $\widehat{\boldsymbol{x}}$. It can be done by solving the Candidate Maximum Regret problem (CMR) [51].

As previously discussed, x^* is the solution that minimizes the maximum regret for all $\boldsymbol{x} \in \Omega$, so $R_{max}(\widehat{\boldsymbol{x}}) \geq R_{max}(x^*)$ is an upper bound for the MMR problem. Therefore, it is possible to build an iterative algorithm using MMR to generate candidate solutions whose maximum regret is assessed in CMR, as shown in figure 1. As soon as the CMR upper-bound $R_{max}(\widehat{\boldsymbol{x}})$ is equal to or lower than MMR lower-bound $\widehat{\boldsymbol{r}}$, the algorithm has converged to $\widehat{\boldsymbol{x}} = x^*$.

However, a significant issue is that CMR is a quadratic objective function problem. Mausser and Laguna [51] describe a mathematical programming procedure consisting of an improved formulation from [50], in which the authors obtain the following formulation for the CMR problem:

$$
\begin{aligned}
R_{max}(\hat{\boldsymbol{x}}) \equiv max \quad & \overline{c}z - \underline{c}y \\
\text{s.t.} \quad & \boldsymbol{x} \in \Omega \\
& x + y - z = \hat{\boldsymbol{x}} \\
& y_i - \hat{x}_i b_i \leq 0 & \forall i \in \Psi \\
& z_i - (M_i - \hat{x}_i)(1 - b_i) \leq 0 & \forall i \in \Psi \\
& z_i - y_i \geq -\hat{x}_i & \forall i \notin \Psi \\
& z_i - y_i \leq M_i - \hat{x}_i & \forall i \notin \Psi \\
& \boldsymbol{y}, z \geq 0 \\
& b_i \in \{0,1\} & \forall i \in \Psi
\end{aligned}
\tag{5}
$$

where y_i and z_i are non-negative variables, b_i are binary variables to enforce the complementarity slackness condition between y_i and z_i ($y_i z_i = 0$), and M_i is an upper bound to x_i.

The proposed CMR formulation utilizes the **c**-*consistency* property [50], which limits the consideration of uncertain costs ***c*** to only their extremal values. In conjunction with x-*optimality*, this allows for the restriction of the decision variable ***x*** to solely those vertices of the feasible region Ω that are optimal under the extremal values of ***c***.

Moreover, **c**-*consistency* implies that additional constraints involving y_i, z_i and b_i variables are only needed for $i \in \Psi$, since the regret term for certain costs is already linear. However, for the sake of simplicity, additional equations are also included for $i \notin \Psi$. Note that the regret maximizing cost scenario $\hat{\boldsymbol{c}}$ would be set as $\hat{\boldsymbol{c}} = \overline{c} + b_i(\underline{c} - \overline{c})$.

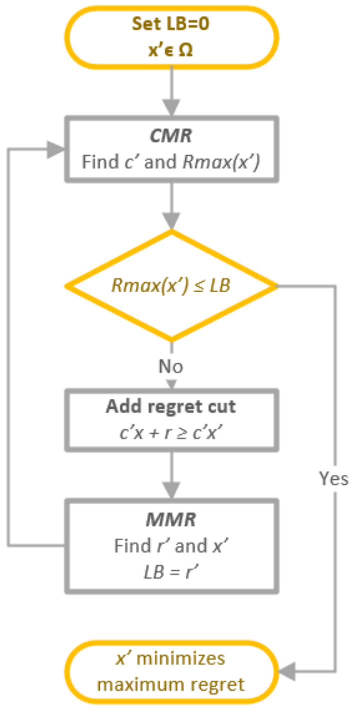

Figure 1 Minimax regret algorithm flowchart, which obtains the minimax regret for linear programs with interval objective function coefficients: Lower Bound parameter (LB), Minimizing maximum regret decision (x'), Candidate Maximum Regret problem (CMR), Maximizing cost scenario (c'), Maximum regret (Rmax), Minimax Regret problem (MMR), Minimax regret (r)

Thus, the minimax regret algorithm integrated into the novel decision-making approach is depicted in Figure 1. The algorithm commences with an initial solution and iteratively proposes a candidate solution in the MMR model. It then identifies the cost scenario that maximizes the regret of that candidate solution in the CMR model. At each iteration, a regret cut is incorporated into the MMR problem, reducing the feasible region of the candidate solutions. Consequently, the algorithm ultimately converges by utilizing both models' upper and lower bounds.

3.3. A novel decision support method based on robust optimization and minimax regret

The joint application of both methods is not immediate. Combining the minimax regret iterative algorithm with the B&S technique generates distortions in the results: incorporating the additional variables *W* and *P* (employed in the robust counterparts of the constraints) into the CMR maximization problem leads to an inappropriate behaviour of these variables, which adopt values to further minimize the maximum regret, instead of supporting the uncertain parameters to take their worst realization as the protection level τ increases. To prevent this, the model is first solved by applying the B&S technique in the constraints. Afterwards, when applying the minimax regret algorithm, these additional variables, *W* and *P,* are fixed for the robust counterparts in the constraints.

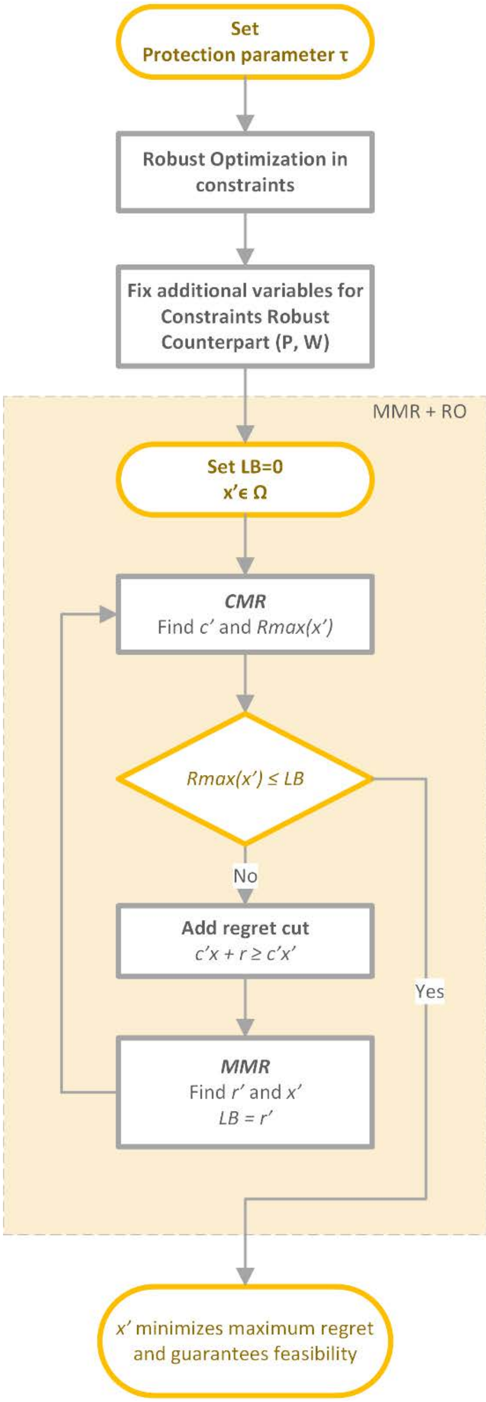

Figure 2 Flowchart of the decision support method, which enables the determination of the minimax regret decision for optimality while ensuring feasibility in the constraints: Protection parameter (τ), Robust optimization additional parameters (P, W) Lower Bound parameter (LB), Minimizing maximum regret decision (x'), Candidate Maximum Regret problem (CMR), Maximizing cost scenario (c'), Maximum regret (Rmax), Minimax Regret problem (MMR), Minimax regret (r)

Figure 2 shows the final procedure, in which the sequence of steps entails applying robust optimization (i.e., B&S technique) initially to compute the additional variables *W* and *P* for the corresponding protection level. Subsequently, the minimax regret algorithm is utilized in conjunction with the robust counterpart of the constraints, in which *W* and *P* additional variables have been fixed to the previously determined values. The approach does not involve prioritizing one criterion over the other, as both criteria are entirely complementary and implemented concurrently, as shown in section 4.

The resulting algorithm allows obtaining a decision that minimizes the maximum regret in the face of uncertainties in the objective function, such as costs, while also safeguarding against worst-case realizations of uncertainties in the constraints, such as demand or resource availability. It is crucial to note that this algorithm can be tailored to the specific preferences of decision-makers, based on their risk aversion, degree of conservatism, or concern for regret. This adaptability can be achieved by adjusting the protection level τ and the uncertainty sets to consider a broader or more restricted range of possibilities, given that both methodologies rely on uncertainty sets. Regarding the latter, it would allow considering extreme events, such as shocks in demand (e.g., as happened with the COVID-19 pandemic) or energy cost spikes (e.g., as has happened following the Ukraine war).

The generality of the methodology deserves special attention, as it holds significant implications for its broad applicability across various domains. Specifically, this methodology can be adapted to any model that requires a robust energy planning and can incorporate diverse policies and systems in an explicit manner. As a result, it has the potential to be applied to any country, provided that the necessary data is available (which is a reasonable assumption for most cases) and there exists adequate expertise to accurately understand the model (which is also a reasonable assumption). There are no inherent limitations pertaining to the methodology itself. Actually, its applicability even extends beyond energy planning optimization models and could encompass other optimization models from diverse disciplinary backgrounds.

4. Assessment of the robust, minimax regret algorithm proposed

The novel decision support method has been implemented in the context of MASTER, a real-size strategic energy planning model similar to MARKAL-TIMES. MASTER is a bottom-up, partial equilibrium, linear programming (LP) model that operates to facilitate sustainable energy policy analysis. The present work utilizes a dynamic version of the MASTER model that meets the exogenous final energy demand across all demand sectors, while conforming to technical and policy limitations, including greenhouse gas emission reduction targets. MASTER seeks to minimize an objective function representing the total private economic costs of energy supply. The model is programmed using GAMS and solved using CPLEX. Further information about the MASTER model can be found in Section 3 of Supplementary Material, as well as in [32].

It is worth noting that since MASTER is a cost-minimization model, the formulation of the minimax regret algorithm (based on a maximization model) can easily be replicated by changing the sign of the objective function coefficients.

It should also be noted that comparing the results of the new algorithm with those of other previous models would not be practical, given the differences in scenarios, parameters, or scope of the analysis. Hence, the improvements offered by the novel algorithm are shown by comparing it to previous, more limited methodologies (RO or MMR) applied to the same model and scenarios.

4.1. Testing the applicability of the decision support method: A case study for the Spanish energy system

In order to prove the applicability of the decision support method in a realistically-sized strategic energy planning model, a case study has been conducted on the Spanish energy system.

The uncertainties considered in the objective function include (i) the investment costs of energy technologies and (ii) the price of fuels. Regarding constraints, the uncertainty considered corresponds to the hourly demand for final energy vectors across demand sectors. For this analysis, the problem is simplified without loss of generality by assuming that all uncertainties are defined by a set of ±20% variation around nominal values. Further information about uncertainty set characterization for energy planning models can be found in [52].

The case study was conducted under a constraint of annual emissions of 29 MtCO2 from 2050, which aligns with the Long Term Strategy 2050 formulated by the Spanish government for achieving climate neutrality [53]. Additionally, a carbon budget constraint was imposed on all emissions during the 2020-2050 period, i.e., cumulative CO2 emissions cannot exceed a certain limitation. Detailed information about the calibration of this case study can be found in section 5 of Supplementary Material.

In terms of computational load, incorporating the proposed algorithm increases the size of the model substantially, but is still feasible and solvable within reasonable times. The iterative method (named *MMR-RO* in Table 2), which comprises both MMR and CMR, as presented in section 3, results in a larger model size due to the addition of numerous constraints and variables. The CMR model corresponds to a MIP model, while the MMR model is an LP model similar in size to the deterministic one. Consequently, the execution time of the novel method is considerably higher, not only because the models are more intricate, but also due to the number of iterations required for the convergence.

Interestingly, the number of iterations needed for τ = 0 is significantly higher than those required for subsequent protection levels, as shown in Table 3. This disparity can be attributed to two main factors. Firstly, the feasible space is comparatively smaller at higher protection levels, and the problem may converge faster. Secondly, the solver can utilize previous solutions to hasten the convergence rate. However, setting a more appropriate initial solution can mitigate this second factor.

Table 2 Models characteristics

Model		Type	Variables	Equations
Det		LP	607,020	452,205
MMR-RO	MMR	LP	721,596	559,941
	CMR	MIP	8,954,131	9,064,274

Table 3 Execution time and iterations for different levels of protection

Tau	Time (sec)	Iterations
Det	117	N/A
τ = 0	196,479	11
τ = 1	14,506	2
τ = 2	14,847	2

The results generated in this realistic exercise are reasonable and correspond to the decision criteria introduced. Regarding the cost, an expected increase in the application of protection levels for robust optimization is observed in Table 4. The Price of Robustness (PoR) indicator, presented in [17], shows the cost of enhancing the robustness of the decision, providing a means to quantify the trade-off between robustness and cost. Specifically, the PoR indicator is derived from the objective function value and is calculated as the difference between the total cost of the robust solution and that of the deterministic nominal case. It is also quantified as a percentage, allowing for a comprehensive analysis of the relative magnitude of the difference and enabling researchers and decision-makers to assess the relative significance of the variations and make informed comparisons between different scenarios or approaches.

The results reveal that, as examined in the subsequent section 4.2, this additional cost of robust solutions (i.e., PoR) leads to a remarkable enhancement in performance by substantially mitigating the likelihood of encountering infeasibilities within the range of uncertainties, while minimizing the opportunity cost. Consequently, it becomes evident that despite their modest 10% increase relative to the nominal case, robust solutions enable a substantial reduction in the overall system cost compared to the worst-case scenario. This preliminary insight already offers a glimpse into the advantages of the robust decision-making compared to Wald-robustness-oriented solutions, such as the deterministic pessimistic case.

Table 4 Economic indicators in the case study of the Spanish energy system

Economics indicators	**Total cost** *[G€]*	**PoR** *[G€]*	**PoR** *[%]*
Det (nominal case)	574.15	-	0.0%
τ = 0	575.74	1.60	0.3%
τ = 1	619.01	44.87	7.8%
τ = 2	633.54	59.39	10.3%
Det (worst case)	732.63	N/A	N/A
Det (best case)	476.39	N/A	N/A

On the other hand, there is a positive correlation between the protection level and the installed capacity increase, as shown in Table 5. This outcome is expected since the exogenous demand is defined as final energy, so the model cannot invest in more efficient energy services supply technologies to reduce demand (e.g., vehicles that reduce fuel consumption to meet the same demand for mobility). Therefore, the model increases conversion capacity as a protective measure to mitigate uncertainty.

When comparing the solutions between the deterministic (*Det*) nominal case and decision τ = 0, which incorporates the minimax regret algorithm, notable distinctions emerge depending on the applied criterion. This comparison underscores the sensitivity of decision outcomes to decision-makers' preferences concerning the minimax regret criterion. Remarkably, the decision at $\tau = 0$ effectively addresses cost uncertainties by increasing the overall installed capacity. Specifically, it favors investments in gas-based technologies, such as OCGT for electricity production and regasification terminals for LNG import, over renewable energy sources. Multiple factors support the rationale behind this decision. Firstly, the significant role of gas prices in determining the opportunity cost contributes to the justification of this choice. Furthermore, the lower investment costs associated with gas-based technologies, in contrast to renewables, provide additional influence in shaping the decision-making process.

In addition, the outcomes for deterministic scenarios, representing both the worst and best realizations of uncertainties, are included. Within the pessimistic scenario, the optimal decision involves excluding gas from the energy mix, reaffirming the notable influence of gas prices. Biomass, wind, and solar PV technologies predominantly replace gas-fuelled systems, with biomass capacity doubling compared to the nominal case. At this point, it becomes apparent that decisions driven by pessimistic scenarios can result in extreme choices. As exemplified in this case, such decisions may entail completely excluding an energy vector, relying solely on a scenario that could potentially prove disastrous if the gas price does not align with the worst-case assumption or if the investment costs associated with renewable technologies exceed those of other well-established technologies. This highlights a crucial distinction where the reliance on pessimistic scenarios can lead to drastic outcomes with potentially adverse consequences. Nevertheless, robust solutions show a diversification of the energy mix, effectively averting the possibility of making potentially catastrophic decisions. This approach promotes the distribution of resources across multiple avenues, thereby enhancing system resilience and mitigating the potential negative consequences of relying excessively on a limited range of energy options.

However, it should be noted that the uncertainty ranges defined in this case study were based on a set of ±20% variation around nominal values. Thus, these results may not represent a treatment of uncertainties consistent with real uncertainty ranges.

Table 5 Capacity for energy conversion technologies in the case study of the Spanish energy system

Conversion energy capacity *[GW]*	2020	2050					
		Det (Nominal case)	**τ = 0**[1]	**τ = 1**	**τ = 2**	**Det** (Worst case)	**Det** (Best case)
Biomass	2	23	25	36	38	46	11
CCGT	27	22	23	29	30	0	23
CHP	5	28	28	29	30	33	22
Coal	8	-	-	-	-	-	-
Fuel Oil	4	-	-	-	-	-	-
Hydro	14	14	14	14	14	14	14
Nuclear	7	-	-	-	-	-	-
OCGT	-	7	12	2	1	0	4
Pumping Storage	3	3	3	3	3	3	3
Solar PV	8	50	48	45	47	61	42
Solar Th	2	-	-	-	-	-	-
Wind	28	71	68	82	85	63	56
Refinery	87	15	15	17	17	17	12
Regasification	76	29	45	46	47	0	31
Biofuel	7	8	8	9	9	9	2
TOTAL	**277**	**270**	**289**	**311**	**321**	**246**	**226**

In summary, the proposed novel method demonstrates its viability for real-size strategic energy planning models. Although the execution time is significantly extended, it remains within an acceptable range for strategic energy planning models, which are typically utilized for long-term exercises. Furthermore, these findings are consistent with previous research, indicating a positive correlation between increased protection and higher costs. Additionally, the obtained results exhibit favourable attributes, leading to well-diversified decisions.

4.2. Evaluating the performance of the decision support method

This section aims to assess the feasibility and optimality performance of the proposed decision support method. Due to the computational complexity of conducting comprehensive analyses

[1] τ = 0 involves solving the min-max regret algorithm for uncertainties in the objective function. Thus, Det and τ = 0 cases do not match.

based on Monte Carlo simulation for the detailed problem presented in the case study (section 4.1), a simplified version was employed.

The complete and original version of the MASTER model, described in section 5 of the Supplementary Material, encompasses the demand for major energy carriers (electricity, biofuels, coal, diesel, gasoline, kerosene, etc.), along with various energy conversion technologies (including nuclear, CCGT, OCGT, hydro, biomass power plants, refineries and biofuel production facilities, among others). However, for these evaluations, the focus was on the simplified version, which only considers electricity demand as the final energy carrier and includes four power generation technologies: wind, solar, combined cycle gas turbines (CCGT), and coal-fired power plants. Notably, emission restrictions were not accounted for in this simplified version.

Feasibility analysis

First, a comparison is made to assess the extent to which the comprehensive methodological approach (*MMR-RO* in Table 6), which integrates both the B&S technique and the minimax regret algorithm, achieves the same robustness in the constraints as the isolated application of the robust optimization technique (*RO* in Table 6) proposed by B&S. For this, a Monte Carlo simulation (N=10,000) has been carried out. The scenarios were generated using a uniform distribution within the uncertainty range. This distribution was chosen to capture the maximum homogeneous diversity of values within the uncertainty set. Nonetheless, it is worth noting that the present analysis could be reproduced with alternative probability functions, as the goal is to compare both cases and determine if the combination of robust optimization and the minimax regret algorithm compromises the feasibility of the decision. Hence, the specific choice of probability function becomes trivial, as long as it remains consistent across all cases.

These simulations were carried out by fixing the investment variables determined by the model, but leaving operation variables free under different realizations of the uncertain variables.

On the other hand, it includes different levels of protection to contrast the results with those of the literature, as well as to expand the comparison and ensure that the conclusions remain valid in case a different level of protection is chosen.

Table 6 Simulation results for feasibility analysis for different levels of protection

τ		0 [2]		1		2		3	
		MMR-RO	RO	MMR-RO	RO	MMR-RO	RO	MMR-RO	RO
Infeasiblities	*[%]*	93.20%	93.10%	30.00%	29.90%	5.00%	5.00%	0.00%	0.00%
Mean	*[k EUR]*	206,336	206,262	217,558	217,411	225,490	225,280	228,295	228,061
PoR	*[k EUR]*	-	-	11,221 (5.4%)	11,149 (5.4%)	19,154 (9.3%)	19,018 (9.2%)	21,959 (10.6%)	21,799 (10.6%)
Std Dev	*[k EUR]*	14,731	14,240	3,720	3,770	2,854	2,892	2,595	2,633
Max	*[k EUR]*	280,728	286,439	244,464	244,290	238,529	238,472	239,552	239,493
Min	*[k EUR]*	190,131	189,915	209,240	208,924	219,878	219,546	223,482	223,138
ENS Mean	*[MWh]*	913,537	914,698	446,891	444,726	300,905	300,905	-	-
ENS Std Dev	*[MWh]*	635,941	632,442	254,135	253,752	84,985	84,985	-	-

It is important to note that the results in Table 6 for the average cost (*Mean*), price of robustness (*PoR*), standard deviation (*Std Dev*), maximum cost (*Max*), and minimum cost (*Min*) have been calculated for feasible outcomes only. Infeasibilities are reflected in a high penalty cost called ENS (*Energy Not Supplied* slack variable), rendering the total system cost uninterpretable in these cases.

This analysis shows that robust optimization (RO) and the novel decision support method (MMR-RO) exhibit very similar behaviour regarding feasibility. Consequently, all the properties achieved through the RO approach are preserved in MMR-RO: (i) the occurrence of infeasibilities is drastically reduced as the level of protection increases; (ii) the Price of Robustness (PoR) of obtaining high levels of protection with negligible infeasibilities is moderate; (iii) the standard deviation is significantly decreased, indicating more stable outcomes for higher protection; (iv) the maximum cost is reduced, although the average and minimum costs increase, as expected due to the incorporation of an additional cost for higher levels of protection; (v) the slack variable ENS, which quantifies the amount of energy that is not supplied to meet demand, reveals that as the level of protection increases, the magnitude of the infeasibility and its variability are considerably reduced. Therefore, the protection against infeasibilities not only mitigates their occurrence but also reduces their impact when they do occur.

[2] For τ = 0, the application of RO represents the deterministic case, while the application of MMR-RO involves solving the MMR algorithm for uncertainties in the objective function. Thus, both cases do not match at the zero-level of protection.

Hence, the proposed methodology guarantees the same protection as robust optimization against infeasibilities in the decision-making process. This finding holds for all levels of protection, offering decision-makers the same flexibility to adjust the level of protection as they would when using only the robust optimization approach.

Furthermore, this analysis also serves as a valuable tool for illustrating the sensitivity of a decision regarding decision-makers' preferences. For instance, decision-makers can assess the additional cost associated with increasing protection (i.e, of being more risk-averse) by quantifying the trade-off between cost and Wald robustness (i.e., PoR versus Infeasibilities). By referring to the findings presented in Table 6, the decision-maker may find satisfaction in a protection level of $\tau = 1$, which reduces infeasibilities to a mere 30% while incurring an extra cost of 5%. Alternatively, they could opt for a higher level of protection, such as $\tau = 3$, where infeasibilities are nearly eliminated but at the expense of a cost increase of 10%. Consequently, the sensitivity of the decision, guided by the decision-maker's preferences, becomes well-defined, showcasing a transparent and clear approach that allows for the selection of varying levels of protection. It is important to note, as discussed in section 3.3, that not only does the degree of protection influence the decision's sensitivity, but also the definition of the uncertainty range, wherein wider ranges offer greater protection.

Optimality analysis

This analysis aims to verify whether the decision produced by the novel method is the one that results in the lowest possible maximum regret under all considered ranges of uncertainty, without exception.

According to the **c**-*consistency* property, presented in section 3, the consideration of uncertain costs ***c*** is limited to their extremal values, i.e., the scenarios of maximum regret will be those in which all uncertainties take one of the two extreme values of their uncertainty set. These scenarios will be referred to as extreme. Now, the evaluation of extreme scenarios is a combinatorial problem of size equal to 2^{Γ}, where Γ is the total number of uncertainties.

The study involves the evaluation of 64 extreme scenarios, which include four uncertain investment costs and two uncertain fuel costs. Those extreme scenarios yield 64 optimal decisions. Thus, the decision from the novel method (*MMR-RO* in Table 7) is incorporated, and build the payoff matrix, which in turn yields the regret matrix.

Table 7 presents the Maximum regret, Maximum total cost, and Minimum total cost indicators for different levels of protection. The minimum (*Min*) and maximum (*Max*) values of these indicators are calculated from the evaluation of the 65 candidate decisions (64 extreme-scenario decisions plus the MMR-RO decision) in the 64 extreme scenarios. Additionally, the outcomes for the decision derived from the proposed method (*MMR-RO* in Table 7) are presented along with its ranking position relative to the other 64 decisions.

Table 7 Simulation results for optimality. All decision variables are fixed.

	Maximum Regret				**Maximum Total Cost**				**Minimum Total Cost**			
τ	0	1	2	3	0	1	2	3	0	1	2	3
Min	6,137	6,873	7,241	7,364	245,206	274,631	289,343	294,247	166,139	186,076	196,044	199,367
MMR-RO	6,137	6,873	7,241	7,364	245,216	274,642	289,355	294,259	166,148	186,085	196,054	199,377
Max	25,896	29,009	30,548	31,076	256,264	287,019	302,385	307,516	173,421	194,234	204,633	208,106
Ranking (out of 65)	1	1	1	1	5	5	5	5	5	5	5	5

The results show that the novel decision support method achieves the expected outcome of minimizing maximum regret for all levels of protection, making it the best decision in terms of this criterion. Additionally, its performance in both maximum and minimum cost is remarkable, within the 10th percentile in both cases. Significantly, these results confirm the absence of negative effects when combining the minimax regret algorithm with robust optimization. Moreover, the obtained results are applicable for all levels of protection, emphasizing that the decision-maker can freely select the desired level of protection without concerns about affecting the decision's outcome regarding the Savage criterion.

In conclusion, this decision-making process ensures the best decision regarding the minimax regret criterion for all levels of protection.

5. Conclusions

In strategic energy planning modelling, as in other fields, it is crucial to deal with epistemic uncertainties affecting the feasibility and optimality of the potential solutions, and to do that according to decision-makers' preferences. This is particularly relevant now, given the large transformation that energy systems have to face in the coming years because of the need to decarbonize in a very short time. Large investments will need to be mobilized in a high-uncertainty environment while still ensuring security of supply, and decision support methods able to deal with all these elements are much needed.

This paper contributes to this field by establishing a theoretical framework for robust decision-making in strategic energy planning. It delves into the distinction between epistemic and probabilistic uncertainties and explores diverse methodologies for handling uncertainty. It introduces a novel nomenclature—Wald, Sensitivity, and Savage robustness—proposed for the first time in this study to differentiate various interpretations of robustness in the literature. Emphasizing the alignment of decision criteria with decision-makers' preferences, this study critically evaluates the challenges in current robust strategic energy planning. It calls for an integrated approach, combining diverse methods to handle uncertainties in the objective function and constraints, providing a robust theoretical foundation for strategic energy planning.

Aligned with this perspective, this paper introduces a novel decision support method, marking the first proposal to integrate two distinct decision-making methodologies within a single algorithm to handle epistemic uncertainties. Specifically, it combines a conservative approach for uncertainties affecting constraints with a minimax regret approach for those impacting the objective function. This approach facilitates energy modelling exercises that can be more closely aligned with real-world decision-makers' preferences for both feasibility and optimality. Crucially, this is achieved without resorting to probabilistic approaches, which are deemed inappropriate for dealing with this type of uncertainty. This combination of methodologies is achieved while retaining the separate advantages of each one, without any detrimental effects of their application together in a single algorithm.

The practical applicability of the proposed decision support method is demonstrated through its application to a real-size strategic energy planning model, proving its applicability for use in other similar models (including others in other disciplines). The ex-post evaluations indicate that this approach maintains the robust optimization performance for reducing both the occurrence and magnitude of infeasibilities, while also satisfying the minimax regret criterion for the entire range of uncertainties in the objective function.

Of course, some limitations do remain. The current computing time, while still within reasonable limits, could be improved further, for which several solutions are currently being explored: a better initial solution may be provided; it may also be possible to apply a heuristic methodology to speed up the convergence of the minimax regret algorithm, such as the one proposed in [54].

Looking forward, further research avenues include a deeper exploration of flexibility as a critical preference for decision-makers facing deep uncertainty and a significant attribute of robust systems. Leveraging the dynamic nature of energy models, future investigations can assess decision changeability and adaptability. Moreover, testing the novel methodology with diverse foresight approaches, which often exhibit myopic assessments of uncertainties, holds promise for advancing the understanding and application of the proposed approach. The inclusion of a detailed exploration into the correlation among uncertain parameters emerges as a vital aspect of future research to enhance the overall robustness of the proposed methodology.

6. References

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Improving robustness in strategic energy planning: A novel decision support method to deal with epistemic uncertainties

Supplementary Material

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1. Review of application of uncertainty treatment methods to the main energy models

Authors	Model Family	Method	Uncertain parameters	Application	Time dimensioning	Ref
Kanudia & Loulou (1998)	MARKAL	Stochastic programming	Carbon mitigations measures implementation	Quebec energy-environment system	Multi-stage	[1]
Usher & Strachan (2012)	MARKAL	Stochastic programming	Fossil fuels prices, biomass availability	UK energy system	Two-stage	[2]
Loulou & Lehtila (2016)	TIMES	Stochastic programming	Demand, capacities, costs	National energy systems framework	Multi-stage	[3]
Nijs et al. (2011)	TIMES	Stochastic programming	Fuel price	Belgium energy system	Static	[4]
Loulou et al. (2009)	TIAM	Stochastic programming	Climate sensitivity	World-wide energy and emissions market	Static	[5]
Hunter et al. (2013)	TEMOA	Stochastic optimization	Import prices of coal, oil, diesel and gasoline	Utopia energy system	Two-stage	[6]
Gritsevskyi & Nakićenovi (2000)	MESSAGE	Monte Carlo Simulation, Own algorithm	Technology costs	Global (single-region) energy system	Two-stage	[7]
Pye et al. (2015)	ESME	Monte Carlo simulation	Costs, prices, resource availability	UK energy system	Static	[8]
Dreier & Howells (2019)	OSeMOSYS	Monte Carlo simulation	Costs, CO2 emissions, electricity and diesel consumption	Utopia energy systems	Static	[9]
López-Peña Fernández (2014)	MASTER.SO	Scenario Analysis	Electricity generation (firmness), hydraulicity	Spanish energy system	Static	[10]

2. Review of application of robust optimization methods to energy models

Authors	Method(s) (a)	Uncertain parameters	Application and model type (b)	Criteria and indicator	Time dimensioning	Ref
Mulvey et al. (1995)	Own (scenarios)	Energy demand	Power capacity expansion (linear programming (LP)	Pessimistic Wald (Cost)	Multi-stage	[11]
Janak et al. (2007)	Own	Processing time, demand, prices	Chemical plant scheduling (MILP)	Pessimistic Wald (Cost)	Dynamic (continuous-time formulation [12])	[13]
Babonneau et al. (2010)	BT&N, LDR, own	Pollutant transfer, demand	Environmental and energy planning (LP)	Pessimistic Wald (Cost)	Dynamic (three periods)	[14]
Ribas et al. (2010)	Scenarios [15]	Oil production, demand, prices	Oil supply chain strategic planning (LP)	Savage and Pessimistic Wald (Profit)	Two-stage	[16]
Hajimiragha et al. (2011)	B&S	Electricity prices	Plug-in Hybrid Electric Vehicles (MILP)	Pessimistic Wald (Cost)	Static	[17]
Koo et al. (2011)	Scenarios [18]	Fuel prices, emission targets	Sustainable energy planning (LP)	Pessimistic Wald (Cost)	Static	[19]
Jiang et al. (2012)	B&S, own	Wind power production	Wind and hydro unit commitment (MILP)	Pessimistic Wald (Cost)	Two-stage	[20]
Parisio et al. (2012)	B&S	Conversion efficiencies	Energy hub management (MILP)	Pessimistic Wald (Cost)	Dynamic	[21]
Zhao & Zeng (2012)	Own	Wind production	Wind unit commitment (MILP)	Pessimistic Wald (Cost)	Two-stage	[22]

Dong et al. (2013)	B&S, own	Prices, cost, efficiencies	Energy management planning (FRILP)	Pessimistic Wald (Cost)	Dynamic (three periods)	[23]
Street et al. (2014)	ARO	Generation/transmission outages	Electricity market scheduling (MILP)	Pessimistic Wald (Cost)	Static (single-period)	[24]
Akbari et al. (2014)	B&S	Demand, fuel costs	Building energy system (MILP)	Pessimistic Wald (Cost)	Static	[25]
Yokoyama et al. (2014)	Own	Energy demand	Energy supply systems (MILP)	Savage	Static	[26]
Rager (2015)	B&S, own	Cost, demand, efficiencies	Urban energy system (MILP)	Pessimistic Wald (Cost and Cummulative Exergy Demads (CExD))	Static	[27]
Grossmann et al. (2015)	LDR	Reserve demand	Air separation unit scheduling (MILP)	Pessimistic Wald (Cost)	Multi-stage	[28]
Ruiz & Conejo (2015)	B&S, ARO, own	Demand, generators availability	Electricity transmission planning (bilevel MILP)	Pessimistic Wald (Cost)	Two-stage	[29]
Moret et al. (2016)	B&S	Fuel prices	Household supply, conceptual example (MILP)	Pessimistic Wald (Cost)	Static	[30]
Sy et al. (2016)	Own [31]	Selling prices, demand	Polygeneration system (MILP)	Pessimistic Wald (Profit)	Static	[32]

Nicolas (2016)	B&S	Fuel prices, inv. cost; climate	Integrated Assessment Model (LP)	Pessimistic Wald (Cost)	Dynamic	[33]
Gong et al. (2016)	Own	Feedstock price, biofuel demand	Optimal biomass conversion pathways (MINLP)	Pessimistic Wald (Cost)	Two-stage (ARO)	[34]
Majewski, Wirtz, et al. (2017)	Soyster (1973), own	Demand, fuel prices, emissions	Decentralized energy supply system (MILP)	Pessimistic Wald (Cost)	Two-stage	[35]
Majewski, Lampe, et al. (2017)	Soyster (1973), own	Energy demand, fuel prices	Decentralized energy supply system (MILP)	Pessimistic Wald (Cost)	Two-stage	[36]
Ning & You (2018)	AARO, own	Supply of feedstocks, Demand	Process network planning (MILP)	Bi-criterion: Pessimistic Wald (Cost) and Savage	Two-stage	[37]
Caunhye & Cardin (2018)	ARO	Generator outputs	Power-grid capacity expansion (MILP)	Pessimistic Wald (Cost)	Two-stage	[38]
Trachanas et al. (2018)	Own	Energy saving factors	Energy efficiency strategies (LP)	Savage	Static	[39]
Chen et al. (2019)	Own	Renewables energy resources, multi-load demans	Energy hub operation planning	Pessimistic Wald (Cost)	Two-stage	[40]
Moret et al. (2020)	B&S	Costs, discount rate, technology lifetime, demand	Swiss strategic energy planning (MILP)	Pessimistic Wald (Cost)	Static	[41]

Jeong & Lee (2020)	B&S	Effective capacities, 1-min power fluctuation rate	Korean power system planning (LP)	Pessimistic Wald (Cost)	Static	[42]
Cao et al. (2020)	B&S	Market price	Electric vehicles aggregator (MILP)	Pessimistic Wald (Profit)	Static	[43]
Moret et al. (2020)	B&S	Costs, discount rate, technology lifetime, energy demand, efficiency of technologies, capacity factor of renewables	European power systems planning (MILP)	Pessimistic Wald (Cost)	Static	[44]
Xie et al. (2020)	Own [45]	Load, traffic demand	Expansion planning (MINLP)	Pessimistic Wald (Cost)	Two-stage	[46]

(a) Abbreviations: Ben-Tal and Nemirovski (1999) (BT&N), Bertsimas and Sim (2004) (B&S), linear decision rules (LDR), adjustable robust optimization (ARO), affinely adjustable robust optimization (AARO). "Own" indicates that the paper also introduces a RO framework.

(b) Optimization model types: LP, mixed-integer linear programming (MILP), mixed-integer non-linear programming (MINLP), fuzzy radial interval linear programming (FRILP)

3. MASTER model

This paper utilizes a bottom-up, dynamic, partial equilibrium, linear programming (LP) model called MASTER to analyze sustainable energy policies. The model aims to meet the externally-determined demand for final energy across all sectors, adhering to technical and policy constraints, while minimizing the total private economic costs of energy supply, as well as the social cost of CO2 emissions. This cost can be seen as a measurement of energy sustainability. The model is programmed in GAMS and solved with CPLEX.

While the model's current data structure represents the Spanish energy system, it can be adapted for any other energy sector. The model utilizes a processes and flows approach, inspired by the MARKAL/TIMES models, but has several distinct differences. Firstly, the level of technical complexity is smaller, resulting in increased transparency and reduced reliance on hard-to-understand parameters. Secondly, the code emphasizes transparency and easy interpretation, in contrast to TIMES, which uses closed code and a proprietary graphical interface.

The model is structured using time slices, with 24 time slices for each season, corresponding to a representative day, resulting in 96 time slices per year. This temporal granularity is defined for each year, which represents a five-year period. Executing the model between 2020 and 2050 at five-year intervals generates a representation consisting of 672 time slices.

The model can invest in new capacity for processes, subject to capacity restrictions, resulting in another main output of the model being the corresponding investments in new capacities. While we describe the main equations used in the model, additional information on the sets, parameters, variables, and mathematical formulation of all equations can be found in [10].

Objective function

The objective function is a minimisation of the total economic costs of energy supply. We have also included slack-variable terms for penalising the unsupplied energy, as well as the excess in the emission cap limit from 2050 (net-zero year target) and the excess in the emission budget limit (from the calibration year, 2020, until the net-zero target year, 2050). The elements included as costs in the objective function are:

- Domestic primary energy production cost
- Primary Energy imports cost
- Energy conversion variable cost
- Conversion capacity fixed cost

- New Conversion capacity investment cost
- Decommission Conversion capacity cost
- Energy transportation cost
- Non supplied energy cost (penalisation)
- Emission cap limit excess (penalisation)
- Emission budget limit excess (penalisation)

Constraints

- **Final energy supply in each demand sector**

  For each demand sector, the demand for every final energy commodity must be supplied. The slack variable for Nonsupplied energy is accounted at this equation.
- **Energy balance in each transport process**

  Energy balances must be correctly met in every transport process in all time slices
- **Balance in each conversion process**

  Power balances must be correctly met in every conversion process in all time slices. The only exception is in the storage power processes, which accumulate energy in some time slices to release it in others, and therefore comply with this condition at a seasonal level.
- **Share limitations in power flows outgoing from conversion processes**

  A conversion process can produce more than one flow of final energy. This is typical of oil refineries, which produce gasoline, diesel, kerosene, fuel oil or LPGs, among others. These constraints limit the maximum and minimum shares that each individual outgoing flow can represent in the total output.
- **Conversion processes' capacity limitations**

  Each conversion process must comply with a main capacity limitation: its outgoing power flow (of all types of final energy produced) cannot be bigger than its total installed capacity.
- **Production in conversion processes modelled with availability factors**

  Some conversion technologies are modelled with availability factors (e,g, wind or solar power generators). This constraint establishes the production of each of these processes.
- **Power balance in each primary energy process**

  Power balances must be correctly met in every primary energy process in all time slices. The main idea behind the primary energy process modelling is that all actually used (i.e.

physical) primary energy used in the energy system must come either from domestic primary energy production or from primary energy imports.

- **Domestic primary energy production capacity limitation**

  The amount of primary energy production in the country can be limited, in power terms, through this constraint.

- **Primary energy import capacity limitation**

  The imported primary energy power cannot be bigger than the import capacity

- **Emission cap**

  This constraint sets an annual limit on CO2 emissions from the year declared as Net-zero target (e.g. 2050).

- **Emission budget**

  This constraint sets a limit on the cumulative CO2 emissions from the base year until the year in which the net-zero target is reached (e.g. the period 2020-2050). This constraint can be accounted for by using a dynamic version of the MASTER model.

4. The application of the MMR-RO algorithm formulation to the case study of the MASTER model

Below is the mathematical formulation of the main equations that were modified and added to the MASTER model as part of the proposed methodology. To improve clarity, it should be noted that terms beginning with the letter *p* relate to parameters, while those starting with *v* pertain to variables. Additionally, the superindex denotes different variables or parameters, while the subindex indicates the dimensions (sets). The additional parameters and variables required to construct the methodology are indicated in bold font.

Robust optimization for uncertainties in the constraints

In this particular case study, only uncertainty in the parameter of the exogenous hourly demand for final energy has been taken into account in the constraints. Therefore, only the demand balance equation, which guarantees that demand is met through the energy supply produced by conversion technologies, has been subjected to modification. The original demand balance equation is as follows:

$$vGen_{f,t} + vENS_{f,t} \geq \sum_{d} pDem_{d,f,t} \qquad \forall f \in F, \quad \forall t \in T \qquad (1)$$

where $f \epsilon F$ represents the final energy vectors, $d \epsilon D$ the demand sectors, and $t \epsilon T$ the time slices. The variable *vGen* is the final energy produced by conversion technologies and *vENS* the non-supplied energy, while *pDem* is the parameter for hourly final energy demand across different sectors.

After applying the Bertsimas & Sim method [47] to this balance, the resulting robust counterpart is given by the following two equations:

$$\sum_{g} vGen_{g,f,t} + vENS_{f,t} - \sum_{d} pDem_{d,f,t} - \boldsymbol{\tau} * \boldsymbol{vZ_{f,t}} - \sum_{d} \boldsymbol{vP_{f,d,t}} \geq 0 \quad \forall f \in F, \quad \forall t \in T \quad (2)$$

$$\boldsymbol{vZ_{f,t}} + \boldsymbol{vP_{f,d,t}} \geq \boldsymbol{pDeltaDem_{f,d,t}} \qquad \forall f \in F, \quad \forall d \in D, \quad \forall t \in T \quad (3)$$

Equations (2) and (3) include the control parameter τ, additional variables *vZ* and *vP*, and the parameter *pDeltaDem*, which represents the maximum deviation of the uncertain parameter from its nominal value.

It should be noted that this methodology can be replicated for other uncertainties that affect different parameters in other equations, by following a similar formulation.

Minimax regret algorithm for uncertainties in the objective function

The original objective function of the model seeks to minimize the overall costs of energy supply, while also taking into account the penalty associated with slack variables that arise from the failure to supply demanded energy and exceeding emission cap and carbon budget limits.

$$\begin{aligned}\min vTotCost = \sum_{t} pDisRate_{t} * (&\sum_{p} (pFuelCost_{p,t} * (vImp_{p,t} + vDom_{p,t})) \\ &+ \sum_{g} (pFixom_{g,t} * vTotCap_{g,t}) + \sum_{g} (pVarom_{g,f} * vGen_{g,f,t}) \\ &+ \sum_{g} (pCapex_{g,t} * vNewCap_{g,t}) + \sum_{g} (pDecom_{g,t} * vDecCap_{g,t}) \\ &+ \sum_{f} (pENS_{f,t} * vENS_{f,t}) + pCO2Exc_{t} * (vCapExc_{t} + vBudgetExc_{t})) \quad (4)\end{aligned}$$

where $p \epsilon P$ represents the primary energy vectors, $g \epsilon G$ the conversion energy technologies, $f \epsilon F$ the final energy vectors, $d \epsilon D$ the demand sectors, and $t \epsilon T$ the time slices. The subsequent tables outline the definition of the parameters and variables in the objective function.

Table 1 Objective function parameters' definition

Parameter	Description	Unit
pDisRate	Discount rate	-
pFuelCost	Fuel cost	€/MWh
pFixom	Fixed O&M cost	€/kW
pVarom	Variable O&M cost	€/MWh
pCapex	Conversion energy technology CAPEX cost	€/kW
pDecom	Conversion energy technology Decommission cost	€/kW
pENS	Energy non-supplied cost	€/MWh
pCO2Exc	CO2 excess cost	€/tCO2e

Table 2 Objective function variables' definition

Variable	Description	Unit
vImp	Primary energy importation	GWh
vDom	Primary energy domestic production	GWh
vGen	Final energy generation	GWh
vTotCap	Total conversion energy technology capacity	GW
vNewCap	New conversion energy technology capacity	GW
vDecCap	Decommissioned conversion energy technology capacity	GW
vENS	Energy non-supplied	GWh
vCapExc	Excess emissions beyond the cap limit	tCO2e
vBudgetExc	Excess emissions beyond the budget limit	tCO2e

To apply the iterative minimax regret algorithm, it is necessary to generate the set of equations corresponding to (4) and (5) in section 3.2 of the Manuscript. The implementation of this methodology to the objective function (4) of the MASTER model yields the MMR and CMR models, which are subject to algorithmic iterativity. It is important to highlight that uncertainty in the objective function is solely taken into account for the fuel cost parameter (*pCost*) and the conversion energy CAPEX cost (*pCapex*).

CMR

$\max \boldsymbol{vCMR}$

s.t.

$$\boldsymbol{vCMR} = \sum_t pDisRate_t * (\sum_p \left(\boldsymbol{pFuelCost_{p,t}^{Max}} * \left(\boldsymbol{vImp_{p,t}^{W}} + \boldsymbol{vDom_{p,t}^{W}}\right)\right) + \sum_g (pFixom_{g,t} * \boldsymbol{vTotCap_{g,t}^{W}}) + \sum_g \left(pVarom_{g,f} * \boldsymbol{vGen_{g,f,t}^{W}}\right) + \sum_g \left(\boldsymbol{pCapex_{g,t}^{Max}} * \boldsymbol{vNewCap_{g,t}^{W}}\right) + \sum_g \left(pDecom_{g,t} * \boldsymbol{vDecCap_{g,t}^{W}}\right) + \sum_f (pENS_{f,t} * \boldsymbol{vENS_{f,t}^{W}}) + pCO2Exc_t * \left(\boldsymbol{vCapExc_t^{W}} + \boldsymbol{vBudgetExc_t^{W}}\right) - (\sum_t pDisRate_t * (\sum_p \left(\boldsymbol{pFuelCost_{p,t}^{Min}} * \left(\boldsymbol{vImp_{p,t}^{Y}} + \boldsymbol{vDom_{p,t}^{Y}}\right)\right) + \sum_g (pFixom_{g,t} * \boldsymbol{vTotCap_{g,t}^{Y}}) + \sum_g \left(pVarom_{g,f} * \boldsymbol{vGen_{g,f,t}^{Y}}\right) + \sum_g \left(\boldsymbol{pCapex_{g,t}^{Min}} * \boldsymbol{vNewCap_{g,t}^{Y}}\right) + \sum_g \left(pDecom_{g,t} * \boldsymbol{vDecCap_{g,t}^{Y}}\right) + \sum_f (pENS_{f,t} * \boldsymbol{vENS_{f,t}^{Y}}) + pCO2Exc_t * \left(\boldsymbol{vCapExc_t^{Y}} + \boldsymbol{vBudgetExc_t^{Y}}\right))) \quad (5)$$

$$vImp_{p,t} + \boldsymbol{vImp_{p,t}^{Y}} - \boldsymbol{vImp_{p,t}^{W}} = \boldsymbol{pImp_{p,t}^{MMR}} \quad (6)$$

$$vDom_{p,t} + \boldsymbol{vDom_{p,t}^{Y}} - \boldsymbol{vDom_{p,t}^{W}} = \boldsymbol{pDom_{p,t}^{MMR}} \quad (7)$$

$$vTotCap_{g,t} + \boldsymbol{vTotCap_{g,t}^{Y}} - \boldsymbol{vTotCap_{g,t}^{W}} = \boldsymbol{pTotCap_{g,t}^{MMR}} \quad (8)$$

$$vGen_{g,f,t} + \boldsymbol{vGen_{g,f,t}^{Y}} - \boldsymbol{vGen_{g,f,t}^{W}} = \boldsymbol{pGen_{g,f,t}^{MMR}} \quad (9)$$

$$vNewCap_{g,t} + \boldsymbol{vNewCap_{g,t}^{Y}} - \boldsymbol{vNewCap_{g,t}^{W}} = \boldsymbol{pNewCap_{g,t}^{MMR}} \quad (10)$$

$$vDecCap_{g,t} + \boldsymbol{vDecCap_{g,t}^{Y}} - \boldsymbol{vDecCap_{g,t}^{W}} = \boldsymbol{pDecCap_{g,t}^{MMR}} \quad (11)$$

$$vENS_{f,t} + \boldsymbol{vENS_{f,t}^{Y}} - \boldsymbol{vENS_{f,t}^{W}} = \boldsymbol{pENS_{f,t}^{MMR}} \quad (12)$$

$$vCapExc_t + \boldsymbol{vCapExc_t^{Y}} - \boldsymbol{vCapExc_t^{W}} = \boldsymbol{pCapExc_t^{MMR}} \quad (13)$$

$$vBudgetExc_t + \boldsymbol{vBudgetExc_t^{Y}} - \boldsymbol{vBudgetExc_t^{W}} = \boldsymbol{pBudgetExc_t^{MMR}} \quad (14)$$

$$\boldsymbol{vImp^{Y}_{p,t} - vB_{p}{}^{FuelCost} * pImp^{MMR}_{p,t}} \leq 0 \tag{15}$$

$$\boldsymbol{vDom^{Y}_{p,t} - vB_{p}{}^{FuelCost} * pDom^{MMR}_{p,t}} \leq 0 \tag{16}$$

$$\boldsymbol{vGen^{W}_{g,f,t} - vGen^{Y}_{g,f,t} \geq -pGen^{MMR}_{g,f,t}} \tag{17}$$

$$\boldsymbol{vENS^{W}_{f,t} - vENS^{Y}_{f,t} \geq -pENS^{MMR}_{f,t}} \tag{18}$$

$$\boldsymbol{vTotCap^{W}_{g,t} - vTotCap^{Y}_{g,t} \geq -pTotCap^{MMR}_{g,t}} \tag{19}$$

$$\boldsymbol{vNewCap^{Y}_{g,t} - vB^{Capex}_{g} * pNewCap^{MMR}_{g,t} \leq 0} \tag{20}$$

$$\boldsymbol{vDecCap^{W}_{g,t} - vDecCap^{Y}_{g,t} \geq -pDecCap^{MMR}_{g,t}} \tag{21}$$

$$\boldsymbol{vCapExc^{W}_{t} - vCapExc^{Y}_{t} \geq -pCapExc^{MMR}_{t}} \tag{22}$$

$$\boldsymbol{vBudgetExc^{W}_{t} - vBudgetExc^{Y}_{t} \geq -pBudgetExc^{MMR}_{t}} \tag{23}$$

$$\boldsymbol{vImp^{W}_{p,t} - (pM - pImp^{MMR}_{p,t})} * (1 - \boldsymbol{vB_{p}{}^{FuelCost}}) \leq 0 \tag{24}$$

$$\boldsymbol{vDom^{W}_{p,t} - (pM - pDom^{MMR}_{p,t})} * (1 - \boldsymbol{vB_{p}{}^{FuelCost}}) \leq 0 \tag{25}$$

$$\boldsymbol{vGen^{W}_{g,f,t} - vGen^{Y}_{g,f,t} \leq pM - pGen^{MMR}_{g,f,t}} \tag{26}$$

$$\boldsymbol{vENS^{W}_{f,t} - vENS^{Y}_{f,t} \leq pM - pENS^{MMR}_{f,t}} \tag{27}$$

$$\boldsymbol{vTotCap^{W}_{g,t} - vTotCap^{Y}_{g,t} \leq pM - pTotCap^{MMR}_{g,t}} \tag{28}$$

$$\boldsymbol{vNewCap^{W}_{g,t} - \left(pM - pNewCap^{MMR}_{g,t}\right)} * \left(1 - \boldsymbol{vB^{Capex}_{g}}\right) \leq 0 \tag{29}$$

$$\boldsymbol{vDecCap^{W}_{g,t} - vDecCap^{Y}_{g,t} \leq pM - pDecCap^{MMR}_{g,t}} \tag{30}$$

$$\boldsymbol{vCapExc^{W}_{t} - vCapExc^{Y}_{t} \leq pM - pCapExc^{MMR}_{t}} \tag{31}$$

$$\boldsymbol{vBudgetExc^{W}_{t} - vBudgetExc^{Y}_{t} \leq pM - pBudgetExc^{MMR}_{t}} \tag{32}$$

<u>MMR</u>

$\min \boldsymbol{vRegret}$

s.t.

$$
\begin{aligned}
&\boldsymbol{vRegret} + \sum_t pDisRate_t * (\sum_p \left(\boldsymbol{pFuelCost^{CMR}_{p,t,k}} * \left(vImp_{p,t} + vDom_{p,t}\right)\right) \\
&\quad + \sum_g (pFixom_{g,t} * vTotCap_{g,t}) + \sum_g \left(pVarom_{g,f} * vGen_{g,f,t}\right) \\
&\quad + \sum_g \left(\boldsymbol{pCapex^{CMR}_{g,t,k}} * vNewCap_{g,t}\right) + \sum_g \left(pDecom_{g,t} * vDecCap_{g,t}\right) \\
&\quad + \sum_f (pENS_{f,t} * vENS_{f,t}) + pCO2Exc_t * (vCapExc_t + vBudgetExc_t) \\
&\quad \geq \sum_t pDisRate_t * (\sum_p \left(\boldsymbol{pFuelCost^{CMR}_{p,t,k}} * \left(\boldsymbol{pImp^{CMR}_{p,t,k}} + \boldsymbol{pDom^{CMR}_{p,t,k}}\right)\right) \\
&\quad + \sum_g (pFixom_{g,t} * \boldsymbol{pTotCap^{CMR}_{g,t,k}}) + \sum_g \left(pVarom_{g,f} * \boldsymbol{pGen^{CMR}_{g,f,t,k}}\right) \\
&\quad + \sum_g \left(\boldsymbol{pCapex^{CMR}_{g,t,k}} * \boldsymbol{pNewCap^{CMR}_{g,t,k}}\right) + \sum_g \left(pDecom_{g,t} * \boldsymbol{pDecCap^{CMR}_{g,t,k}}\right) \\
&\quad + \sum_f (pENS_{f,t} * \boldsymbol{pENS^{CMR}_{f,t,k}}) + pCO2Exc_t \\
&\quad * \left(\boldsymbol{pCapExc^{CMR}_{t,k}} + \boldsymbol{pBudgetExc^{CMR}_{t,k}}\right) \qquad \forall\, k \epsilon K \qquad (33)
\end{aligned}
$$

$$
\boldsymbol{vRegret} \geq 0 \qquad (34)
$$

The binary auxiliary variable *vB* is associated with each uncertain parameter (indicated by its superindex), while the superscripts *Y* and *W* represent additional variables necessary for each variable in the original problem. The superscripts MMR and CMR denote the values obtained from the previous iteration of these variables in the CMR and MMR problems, respectively. For instance, in the CMR problem, the parameter $pImp^{MMR}_{p,t}$ represents the resulting value of the variable $vImp_{p,t}$ in the previously solved MMR problem. Similarly, in the MMR problem, the parameter $pImp^{CMR}_{p,t}$ corresponds to the resulting value of the variable $vImp_{p,t}$ in the previously solved CMR problem. The parameter *pM* corresponds to the big M.

Addressing the CMR and MMR models within the iterative algorithm presented in section 3 of the manuscript involves the set of equations (5)-(32) and (33)-(34) respectively.

5. Spanish case study calibration

Section 4.1 features a case study that was conducted to evaluate the viability of the proposed methodology. The uncertainties considered in the objective function include the investment costs of energy technologies and fuel prices. Meanwhile, the uncertainty related to hourly demand for final energy vectors across demand sectors was factored into the constraints. The values used for these uncertain parameters are outlined below. It should be noted that the uncertainty ranges for the case study were trivially defined, with a ±20% variation around nominal values. These nominal values are presented in the tables that follow. In addition to the uncertain parameters, the tables below feature some additional parameters that could provide valuable insights for the analysis of the results. These parameters, namely the previous installed capacity of the Spanish energy system and the efficiency losses of the conversion technologies, are not considered uncertain for the case study.

The time-varying parameters are specified with their initial and final values, which are set to correspond to the years 2020 and 2050, respectively. The values for the years within this time period are calculated using a linear interpolation method. This enables the modeling of learning curves for emerging technologies and the dynamics of fuel prices, which are subject to regulatory changes and shifts in supply and demand.

In order to represent the variation in the exogenous annual demand, an annual growth rate is applied. It is also pertinent to note that the case study's focus on uncertainty is geared towards hourly demand as opposed to annual demand. Hourly demand is derived by utilizing a load curve applied to the annual demand.

Primary Energy	**2020 Fuel cost [€/MWh]**	**2050 Fuel cost [€/MWh]**
Nuclear	2,88	2,88
Imported Coal	10	7
Natural Gas	18,4	18,4
Liquefied Natural Gas	37	37
Crude Oil	40	30
Hydro Run off the River	0	0
Hydro with Reservoir Capacity	0	0
Mihi Hydro	0	0
Wind Onshore	0	0
Wind Offshore	0	0
Solar Photovoltaic	0	0
Solar Thermoelectric	0	0
Solar Thermal	0	0
Biomass Energy Crops	21	21

Biomass Agriculture Waste	17	17
Biomass Forestry Waste	8	8
Solid Waste	21	21
Bioethanol Production Inputs	54	54
Biodiesel Production Inputs	46	46
Biogas	104	104

Conversion Technology	2020 CAPEX Costs [€/kW]	2050 CAPEX Costs [€/kW]	Previous installed capacity [GW]	Conversion losses [%]
Nuclear Power	4800	4500	7,4	0,62
Imported Coal Traditional	1450	1450	3	0,58
Imported Coal Integrated Gasification Combine Cycle	1950	1900	3	0,52
Imported Coal Super-critical Pulverised Coal	1650	1650	1	0,55
Imported Coal Super-critical Pulverised Coal with CCS	3400	2850	0,5	0,64
Combined Cycle Gas Turbine Traditional	550	530	26,6	0,42
Combined Cycle Gas Turbine with CCS	1750	1500	0	0,54
Open Cycle Gas Turbine Traditional	450	450	0	0,55
Open Cycle Gas Turbine with CCS	900	750	0	0,65
Fuel Oil Traditional	784	784	3,7	0,62
Hydro Run off the River	1715	1650	2,15	0
Hydro with Reservoir Capacity	2100	2100	12	0
Hydro with Pumping Storage	3804	3804	3,3	0,3
Mini Hydro	1715	1650	0	0
Wind Onshore	1300	1000	28	0
Wind Offshore	2800	1900	0	0
Solar Photovoltaic Centralised with Tracking	463	355	8,4	0
Solar Photovoltaic Distributed without Tracking in Industry	645	500	0	0
Solar Photovoltaic Distributed without Tracking in Other Uses	645	500	0	0
Solar Thermoelectric Centralised	3000	2800	2,3	0
Solar Thermal Distributed in Industry	848	848	0	0
Solar Thermal Distributed in Other Uses	848	848	0	0
Biomass Energy Crops Centralised	2517	2517	0,32	0,61
Biomass Agriculture Waste Centralised	2517	2517	0,68	0,61
Biomass Forestry Waste Centralised	2517	2517	0	0,61
Solid Waste	5503	5503	0,7	0,61
Cogeneration in Industry. Natural Gas	1425	1425	2,4	0,26
Cogeneration in Other Uses. Natural Gas	2093	2093	2,4	0,27
Cogeneration in Industry. Biomass	2137,5	2137,5	0	0,26
Cogeneration in Other Uses. Biomass	3139,5	3139,5	0	0,27
Refinery Low Complexity	114	114	62,2	0,07
Refinery High Complexity	330	330	24,3	0,09

Refinery Very High Complexity	653	653	0	0,17
Bioethanol Production Plant	1040	1040	0,4	0
Biodiesel Production Plant	510	510	6,7	0
Regasification Terminal	35	35	76	0,01

2020 Annual Demand [GWh/year]	Industry: Chemical	Industry: Mining, Constructions and Materials	Industry: Other	Primary Sector	Residential Sector	Services Sector	Transp. Air	Transp. Land	Transp. Sea
Biodiesel	4,4	172	233	48,4	-	97,2	-	9.476	5,3
Bioethanol	4,4	172	233	48,4	-	97,2	-	9.476	5,3
Biomass	57,8	3.220	14.345	952	29.303	1.332	-	-	-
Coal	1.414	9.039	295	862	755	-	-	-	-
Electricity	6.131	25.462	19.045	4.804	51.087	50.197	-	3.937	-
Heat Distributed	3.065	12.731	9.522	2.402	25.543	25.098	-	-	-
Natural Gas	30.158	44.330	23.372	2.632	34.997	27.014	-	2.777	-
Oil Product Diesel	477	10.069	3.619	24.032	17.355	11.860	-	250.000	5.494
Oil Product Fuel Oil	404	2.076	1.133	145	56,1	101		-	6.565
Oil Product Gasoline	-	-	24	332	-	406	61,5	62.894	-
Oil Product Kerosene	-	-	-	-	-	-	84.475	-	-
Oil Product Liquefied Petroleum Gas	65,7	946	656	696	10.471	2.154	-	1.129	-
Oil Product Other	-	14.362	-	-	-	-	-	-	-

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